# Perceiving, Monitoring, and Taking Control: How System Reliability Shapes Driver Interaction with Automation

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## ABSTRACT

As intelligent systems assume greater autonomy, drivers increasingly act as supervisory controllers rather than manual operators. In driving automation, system reliability may shape how drivers regulate reliance on automation during periods before takeover. This study examined how system reliability influences drivers' reliance-related attentional strategies, subjective perceptions, and takeover performance. Twenty-four licensed drivers participated in a driving simulator experiment using a one-factor between-subjects design, with system reliability manipulated as high or low. Eye-tracking measures were used to assess visual attention to system information and environmental information, together with measures of perceived risk, trust, takeover time, and lateral control. Results showed that drivers in the high-reliability condition allocated more attention to system information, suggesting a stronger tendency to monitor and rely on the automation. They also tended to allocate less attention to environmental information, although this effect was not significant. High reliability was associated with higher perceived risk and lower trust, while takeover performance showed no significant reliability-related differences. These findings suggest that system reliability shapes reliance-related attentional strategies and provide implications for reliability-adaptive interface design.

## CCS CONCEPTS

• Human-centered computing → Human computer interaction (HCI) • Human-centered computing → Empirical studies in HCI • Human-centered computing → User studies

## KEYWORDS

Driving automation system; system reliability; reliance strategies

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## 1 Introduction

The proliferation of intelligent systems has permeated nearly every facet of modern society, fundamentally reshaping the

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nature of Human–AI Interaction (HAI)[1, 13, 22]. As intelligent systems assume greater autonomy, the human role has shifted from an active manual operator to a supervisory controller [12, 19, 21]. Consequently, transitions of control authority between humans and automation have emerged as a central challenge in HAI [4, 11, 18]. For example, in the domain of driving automation systems, drivers must remain ready to re-engage and reclaim manual control when the system encounters its functional limits [2, 3].

In this context, system reliability becomes a new and critical source of uncertainty in HAI [20]. System reliability is defined as the extent to which a system performs its functions consistently without unexpected deviations [8, 29]. Prior research has widely recognized system reliability as a core system characteristic influencing trust in automation and human–automation coordination [8].

However, existing research exhibits a critical limitation. Studies on driving automation systems have primarily examined how system reliability affects outcome-level measures, such as trust, takeover reaction time, and performance [7, 15, 16]. While this body of work has established that reliability plays a crucial role in takeover behavior, this outcome-oriented focus obscures the underlying behavioral processes. Even when similar takeover outcomes are observed, drivers may engage in different monitoring and decision-making processes. Without understanding these differences, which can limit the effectiveness of system design interventions [23, 26].

To address these gaps, the present study investigates how system reliability shapes drivers' attentional strategies in driving automation systems. Using eye-tracking measures, we examine visual attention allocation to capture distinct monitoring patterns: specifically, the trade-off between orienting attention toward the external driving environment (to maintain situational awareness, reflecting a "trust myself" strategy) versus monitoring the system interface (to verify automation status, reflecting a "trust the system" strategy). In addition, we assess drivers' trust, perceived risk, and subsequent takeover performance. By integrating process-level attentional behavior with outcome measures, this study aims to provide a comprehensive account of how diverse user groups interact with systems of varying reliability. Ultimately, these findings inform the design of reliability-adaptive interaction mechanisms that support effective monitoring and safe control authority transitions, with implications extending to broader HAI contexts.

# 2 Method

## 2.1 Participant

We recruited 24 licensed drivers in mainland China (12 males and 12 females; *Mean* age = 28.13 years, *SD* = 3.85). Eligibility required a valid driver's license, right-handedness, normal or corrected-to-normal vision, and no history of neurological disorders or color-vision deficiency.

## 2.2 Experiment Design

We adopted a one-factor between-subjects design, with system reliability manipulated at two levels: high reliability and low reliability. Participants were randomly assigned to one of the two conditions.

## 2.3 Manipulation of System Reliability

To manipulate system reliability, we adopted the experimental paradigm from Sheng et al. [24]. All participants first read a short neutral introduction highlighting that the driving automation they would experience still required human monitoring and occasional takeover. Following this introduction, participants received a standardized system reliability briefing that described the assigned brand's past test performance and independent ranking. Two versions of the briefing were created: High reliability. The assigned brand (WLE) had been tested for 1,000 km across diverse roads and weather conditions with only two instances of human takeover. In addition, the brand was reported to have achieved an overall rank of 2nd place in an independent media evaluation of mainstream driving automation systems. Low reliability. The assigned brand (DID) had been tested for 1,000 km under the same conditions but required nine instances of human takeover. In the independent media evaluation, the brand was reported to rank in 14th place overall.

The participants were told that the simulated driving automation system adopted the algorithms of the corresponding brands. However, across both conditions, the driving tasks and simulator control logic were identical; only the content of the system reliability briefing differed.

## 2.4 Apparatus

The experiment was conducted using a fixed-base driving simulator developed by WIVW GmbH (see Figure1-a). Driving scenarios were created with SILAB 7.1 software (WIVW GmbH) and displayed on three 43-inch screens positioned approximately 1 m from the driver. Each screen had a resolution of 1920 × 1080 pixels, providing a 150° horizontal and 47° vertical field of view to create an immersive driving environment.

Participants could activate or deactivate the driving automation system by pressing a virtual button on a 15.6-inch interactive touchscreen mounted beside the steering wheel. Manual control could also be resumed by turning the steering wheel with at least a 2° change or pressing the brake pedal at least 10% actuation [6]. Eye-tracking data were collected at 60 Hz using a Smart Eye Pro system and Smart Eye Pro 10.2 software (see Figure1-c). All data streams were synchronized using the Human Research Tool (HRT) software by Info Tech.

## 2.5 Driving Task

The driving task simulated a highway driving setting with two scenarios differing only in environmental conditions (daytime vs. nighttime), presented in counterbalanced order. The inclusion of different lighting conditions aimed to increase ecological validity and reduce monotony [25], rather than to introduce an additional experimental factor. Apart from lighting, the task content and hazard events were identical across the two scenarios.

In each scenario, participants first activated the driving automation system, and after approximately 3 minutes of automated driving, they encountered a simulated road construction site (see Figure1-b). A takeover request (TOR) was issued when the vehicle approached the construction zone at a distance of 150 m [2]. The TOR was delivered via an auditory warning tone, requiring drivers to resume manual control. If they failed to respond, the system continued straight ahead and would ultimately collide with the construction barrier. Participants were required to disengage automation, take over control by steering or braking, and safely navigate the vehicle through the construction zone.

## 2.6 Measurement

*2.6.1 Visual Attention Metrics.* To quantify drivers' visual attention allocation strategies, we calculated Glance Proportion (GP), defined as the percentage of total fixation time allocated to specific Areas of Interest (AOIs) [5, 9]. In this study, we defined two primary AOIs to capture distinct monitoring targets: (1) System Information, encompassing the dashboard and center console screen; and (2) Environmental Information, which included the road ahead, rearview mirrors, and roadside. Data were extracted from the 180-second period of automated driving immediately preceding the Take-Over Request (TOR).

*2.6.2 Subjective Measures.* Perceived risk (PR) was measured using the Perceived Risk in Intelligent System Interaction Scale [24]. Trust in the driving automation system was measured using a 12-item scale adapted from [10]. Participants rated each item on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). These scales have demonstrated strong internal consistency ($\alpha > .90$).

*2.6.3 Takeover Performance.* Takeover performance was assessed using two categories of measures: takeover time (TOT) and takeover quality [28]. The TOT was defined as the latency from the onset of the takeover request to the deactivation of the driving automation. Takeover quality was evaluated through lateral control. We calculated mean lateral distance from the lane center (MLD) to index lane-keeping accuracy and the smoothness of steering corrections.




**Figure 1: Overview of the Study. (a) Experimental apparatus. (b) Trial structure in the driving task. (c) Visualization of gaze tracking. (d) Illustration of the takeover scenario. (e) Participant performing the takeover maneuver**

## 2.7 Procedure

Upon arrival at the laboratory, participants read the experimental instructions and had the opportunity to ask questions. They were explicitly informed that the driving automation system was not fully autonomous and that they remained responsible for vehicle safety throughout the task. Next, participants entered the fixed-base driving simulator, performed an eye-tracking calibration, and read a set of introductory materials, including text and images, that explained the assigned system reliability condition.

The entire experimental session lasted approximately 30 minutes. After completing two drives (one in daytime and one at night), participants removed the equipment and exited the simulator. Finally, they were debriefed, compensated, and thanked for their participation.

## 3 Results

***System information.*** System reliability showed a positive nominal effect ($\beta = 0.62$, SE = 0.31, 95% $CI_{OR}$: [1.00, 3.43], $z = 1.98$, $p = .049$, OR = 1.86; see Figure 2). High-reliability drivers allocated a higher percent of time looking at system information compared with low-reliability drivers.

***Environmental information.*** No significant differences emerged between reliability groups ($\beta = -0.22$, SE = 0.27, 95% $CI_{OR}$: [0.47, 1.35], $z = -0.83$, $p = .406$, OR = 0.80). However, high-reliability drivers showed a tendency to allocate a lower percent of time looking at the roadside compared with low-reliability drivers.

***PR.*** A significant effect of reliability was observed for PR ($\Delta = 0.61$, SE = 0.21, 95% CI [0.18, 1.04], $t(22) = 2.85$, $p = .007$). High-reliability participants reported higher PR than low-reliability participants.

***Trust.*** A marginally significant effect of reliability was observed for Trust ($\Delta = -0.53$, SE = 0.28, 95% CI [−1.09, 0.03], $t(22) = -1.89$, $p = .065$). High-reliability participants reported lower Trust than low-reliability participants.

***Takeover time.*** No significant differences emerged between reliability groups for Takeover time (Δ = −0.63, SE = 0.36, 95% CI: [−1.36, 0.11], t(22) = −1.73, $p$ = .091).

***Takeover performance.*** No significant differences emerged between reliability groups for MLD (Δ = 0.07, SE = 0.04, 95% CI: [−0.02, 0.15], t(22) = 1.55, $p$ = .128).

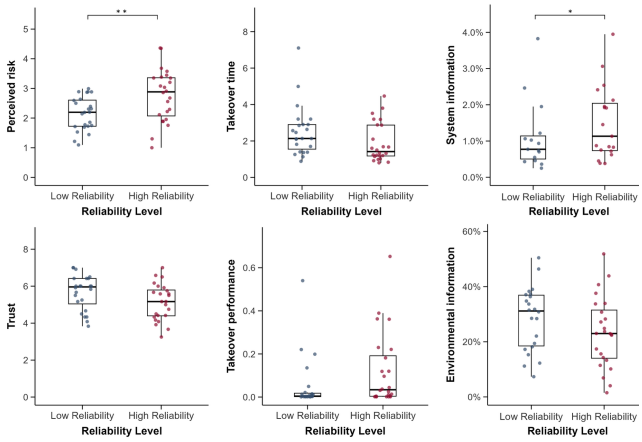



**Figure 2 Effects of system reliability. Notes: * $p$ < .05, ** $p$ < .01, *** $p$ < .001.**

## 4 Discussion

In this study, we identify a reliability-based mechanism linking drivers' subjective perceptions, attentional strategies, and takeover behavior. The findings reveal how drivers regulate their reliance on driving automation systems under different levels of system reliability. Specifically, system reliability appears to shape whether drivers rely on the automation or shift toward more self-directed situation assessment.

Under low system reliability, drivers reported higher trust and lower perceived risk, suggesting that drivers may not evaluate automated systems solely based on their nominal reliability, but also consider the potential consequences of becoming overly dependent on the system. This pattern is not consistent with trust–reliance models, which suggest that when automation is perceived as unreliable, users reduce reliance on the system and assume greater responsibility for monitoring, situation assessment, and control [8, 17, 27]. However, a highly reliable system may encourage drivers to allocate less attention to the driving environment and rely more heavily on automation, which could increase their perceived vulnerability if a system failure occurs. In contrast, when the system is perceived as less reliable, drivers may maintain greater vigilance and a stronger sense of control, thereby reducing their subjective risk perception.

The eye-tracking results provide process-level evidence for reliability-based reliance regulation by revealing distinct monitoring patterns across reliability conditions. Drivers in the high-reliability condition allocated more visual attention to system information than those in the low-reliability condition, suggesting a more interface-oriented monitoring strategy. This pattern can be interpreted as a "Relying on the System" strategy, in which drivers monitored the automation interface to follow or confirm system operation. By contrast, reliability did not significantly affect attention to environmental information, although drivers under high reliability tended to spend less time looking at the roadside. Thus, high reliability may not eliminate environmental monitoring, but it may shift the balance of attention from the external driving environment toward the automation system. This gaze pattern suggests that reliability shapes how drivers regulate reliance at the attentional level: high reliability promotes system-oriented monitoring, whereas low reliability may preserve greater environmental verification and self-monitoring.

This attentional shift was partially reflected in takeover behavior, although the reliability-related differences did not reach statistical significance, probably connected to the limited sample size. Descriptively, drivers under high-reliability conditions tended to show shorter takeover time but greater mean lane deviation. This pattern suggests that faster takeover responses should not necessarily be interpreted as better takeover performance. Under high system reliability, drivers may rely more strongly on the automation and engage less in continuous monitoring, which could reduce their situation awareness before a takeover event. Consequently, when a takeover request occurs, they may initiate manual control quickly, but the response may be more abrupt and less stable, leading to greater deviation from the lane center. Thus, the observed pattern may reflect a speed–control trade-off: high reliability may facilitate rapid response initiation while simultaneously weakening the quality of vehicle stabilization after takeover.

Together, these findings suggest that system reliability does not merely affect drivers' general attitudes toward automation; it also shapes how drivers strategically regulate reliance during human–automation interaction. Low reliability may encourage vigilance, verification, and preparation for manual control, whereas high reliability may promote greater reliance on the automated system. By contrast, high reliability may promote stronger reliance on automation, but such reliance may also reduce continuous monitoring and increase concerns about overreliance. This may explain why high reliability did not uniformly lead to lower perceived risk or higher trust. In addition, although the behavioral differences were not statistically significant, the descriptive pattern of shorter takeover time but greater lane deviation under high reliability suggests a potential speed–control trade-off. This reliability-based regulation of reliance provides a useful mechanism for understanding the link between perceived risk, trust, attention allocation, and takeover performance.

The present findings offer several implications for the design of driving automation systems. From an interface design

perspective, designers should enhance reliability transparency [14, 30], ensuring that drivers understand not only the general reliability of the system, but also when the system may become less capable and when manual readiness is required. Adaptive interfaces may be particularly valuable in this regard. For example, systems could provide staged takeover prompts, clearly communicate changes in system capability, or highlight control-relevant environmental information when reliability decreases. Such designs may help drivers maintain an appropriate level of reliance and prepare more effectively for manual control.

Beyond driving automation, these implications may generalize to a broader class of intelligent systems in which users supervise automated agents under uncertainty. In such systems, designs that support users' regulation of reliance may foster more effective human–AI interaction, particularly when system reliability varies across contexts.

## 5 Conclusion

This study examined how system reliability shapes drivers' interaction with driving automation systems by linking subjective perception, attentional strategies, and takeover behavior. Our findings reveal a reliability-based mechanism of reliance regulation, showing that drivers adaptively decide whether to rely on themselves or on the automation. Under low system reliability, drivers appeared to shift reliance toward themselves, maintaining greater vigilance, verification, and perceived control, which may explain their higher trust and lower perceived risk. Under high system reliability, drivers showed stronger reliance on the automation, as reflected in reduced attention to the external environment, but this reliance may also increase vulnerability during unexpected control transitions. Although reliability-related differences in takeover behavior were not statistically significant, the descriptive pattern of shorter reaction times but greater lane deviation under high reliability suggests a potential speed–control trade-off. By highlighting this mechanism, the study provides actionable implications for reliability-adaptive system design and driver training, which are essential for improving the safety and acceptance of driving automation systems.

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