Human Responses to Network Latency in Level 4 Autonomous Vehicle Teleoperation: From Perception–Control Breakdown to Trust Decay

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Abstract

Network latency disrupts the perception–action loop in teleoperated Level 4 autonomous vehicles, compromising safety and eroding trust. QoS metrics can flag connectivity degradation, but they do not capture the operator's cognitive difficulty or passengers' anxiety. We propose a multimodal approach integrating vehicle telemetry with operator and passenger eye tracking and physiological signals to decode the human impact of network delay during cut-in scenarios. In a high-fidelity simulation study ($N = 51$), our model achieved robust delay classification ($AUC = 0.8175$) and uncovered behavioral markers across the loop. Under delay, operators exhibit a Perception–Control Breakdown marked by heightened perceptual uncertainty and over-correction, followed by Cognitive Reconfiguration in which scanning strategies simplify into rigid, lower-entropy patterns. Passengers show evidence of Trust Decay and an Attentional Lock-in effect during recovery. We conclude with latency-aware interface guidelines including predictive displays, intent-level interaction, event boundary visualization, and explainable feedback to restore the human connection when the network falters.

CCS Concepts

• **Human-centered computing → HCI design and evaluation methods**; **Empirical studies in HCI**; • **Applied computing → Transportation**.

Keywords

Teleoperation, Autonomous Vehicles, Network Latency, Eye-tracking, Physiological Computing, Situation Awareness, Passenger Trust

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1 Introduction

Level 4 autonomous vehicles (AVs) promise a future of driverless mobility, yet they remain constrained by their Operational Design Domains (ODD) [3]. To bridge the gap between autonomous capability and complex real-world edge cases, remote teleoperation serves as the critical "human-in-the-loop" safety fallback [19]. However, this reliance on wireless networks introduces a fundamental vulnerability: latency. Unlike onboard driving where perception and action are coupled instantaneously, teleoperation is susceptible to network degradation (jitter, packet loss) that disrupts the remote operator's control loop [1]. When latency strikes, particularly during critical dynamic events like a sudden vehicle cut-in, it does not merely delay the video feed; it fundamentally alters the operator's cognitive strategy, forcing a reliance on mental prediction over visual perception [11], while simultaneously eroding the onboard passenger's trust in the vehicle's safety and shaping how occupants recover their attention after a near-miss [22].

Current approaches to mitigating teleoperation latency typically rely on technical Quality of Service (QoS) metrics or basic vehicle kinematics [21]. While these indicators effectively flag network

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degradation, they fail to capture the subtle, real-time human costs of delay: the cognitive load of an operator frantically scanning for positional cues, or the physiological stress response of a passenger who perceives the vehicle's instability, and the lingering attentional rigidity that can persist into recovery [22]. By fusing vehicle telemetry with physiological and behavioral sensing, we aim to go beyond simple error detection to characterize the fundamental shifts in operator strategy and passenger comfort, providing the empirical foundation necessary to redesign the teleoperation.

This study makes two primary contributions to the field of human-computer interaction (HCI) and AV teleoperation. First, we demonstrate that network latency creates a unique, detectable, and robust "multimodal fingerprint" across vehicle dynamics, operator behavior, and passenger physiology. Our analysis shows that operators exhibit a coupled *Perception–Control Breakdown* under delay—marked by heightened perceptual uncertainty and control instability—and subsequently undergo *Cognitive Reconfiguration*, shifting from flexible monitoring to simplified, lower-entropy scanning strategies during recovery. Second, extending beyond the remote operator, we show that latency alters the onboard passenger experience through both physiological *Trust Decay* and an *Attentional Lock-in* pattern that suppresses post-event recovery. Translating these insights into design, we propose a set of guidelines for latency-aware interfaces through four targeted interventions: predictive displays, intent-level interaction, event boundary visualization, and explainable feedback.

2 Related Work

2.1 Teleoperation Latency and Driving Performance

The impact of network latency on teleoperation is well-documented in robotics and automotive research. Studies have consistently shown that delays in the visual-motor loop lead to "move-and-wait" strategies, increased lane deviation, and reduced operating speeds [1, 16]. Traditional approaches to mitigating these effects focus on technical QoS metrics, such as optimizing bandwidth or using predictive control algorithms to stabilize vehicle dynamics [18]. However, research in AVs take-overs demonstrates that human "stabilization time" is a distinct and critical phase heavily influenced by driver tendencies [12], a factor often overlooked in teleoperation QoS metrics. Recent work has begun to explore interface aids, such as predictive displays, but often evaluates them based on task completion time rather than the operator's cognitive state or perceptual strategy [10].

2.2 Multimodal Sensing of Operator and Passenger States

To understand the human factor, HCI researchers have increasingly turned to multimodal sensing. Eye-tracking has been used to measure operator situation awareness and cognitive load, with findings suggesting that gaze dispersion increases under high workload [7, 9, 13, 23]. Physiological measures such as heart rate variability (HRV) and electrodermal activity are widely used indicators of stress and workload in human–machine interaction contexts, including automated and remote systems [8, 17]. However, a significant gap remains: while studies investigate the remote AV operator or passenger trust in isolation, few examine them jointly within the same feedback loop [4, 14]. Current research lacks a holistic model that correlates specific network latency patterns with coupled operator Perception–Control Breakdown and post-event Cognitive Reconfiguration, while simultaneously capturing passenger outcomes such as Trust Decay and disrupted recovery (e.g., Attentional Lock-in). This study addresses this limitation to inform more adaptive interface designs.

3 Methodology

Our methodological framework, summarized in Fig. 1, combines a high-fidelity teleoperation simulation with a multimodal analysis pipeline to capture the complete human-machine control loop. By synchronizing vehicle telemetry with operator and passenger states, we aim to formulate objective indices of perceptual uncertainty and trust. The study protocol was approved by a designated Institutional Review Board (IRB), and all participants provided written informed consent prior to the experiment.

3.1 Experimental Design and Participants

We utilized the CARLA simulator [5] to create a controlled environment. We recruited 51 participants (35 female, 16 male; mean age = 41.6, *SD* = 12.0) to act as passengers inside the ego-vehicle. To eliminate confounding variables from varying driving skills, the vehicle was teleoperated by six trained research staff members randomly assigned to passengers, using a standardized protocol to maintain a consistent baseline style. The experiment followed a counterbalanced within-subjects design to mitigate learning effects, featuring two conditions: Normal, representing optimal network operation (RTT < 50 ms), and Delay, where three network parameters were degraded to simulate a realistic bundled failure (mean RTT = 300 ms, jitter = ±100 ms, 2% packet loss). The core task involved a critical cut-in event, where an adjacent vehicle invaded the ego-vehicle's lane, forcing the remote operator to react under varying network qualities.

3.2 Multimodal Data Collection and Feature Engineering

We constructed a synchronized multi-sensor architecture to capture the holistic state of the operator-vehicle-passenger system. Vehicle telemetry was recorded at approximately 19 Hz via the CARLA API, capturing driving dynamics such as speed, steering angle, throttle inputs, and lane deviation metrics. Simultaneously, we monitored the human elements of the loop. For the remote operator, a suite of eye- and head-related measures was recorded at 30 Hz using the Eyeware GazeSense system [6], including gaze dispersion and head kinematics. For the passenger, we used a Smart Eye Pro eye-tracker (60 Hz) [20] to capture multiple ocular and attentional measures, including attention indices and blink-related metrics, synchronized with a single-lead electrocardiogram (ECG) recorded at 1000 Hz using a Biopac MP160 system [2]. The ECG data allowed us to detect R-peaks and derive standard HRV features (e.g., pNN50), providing an objective index of physiological stress [15]. Complementing these sensors, face and cabin cameras were recorded at both stations

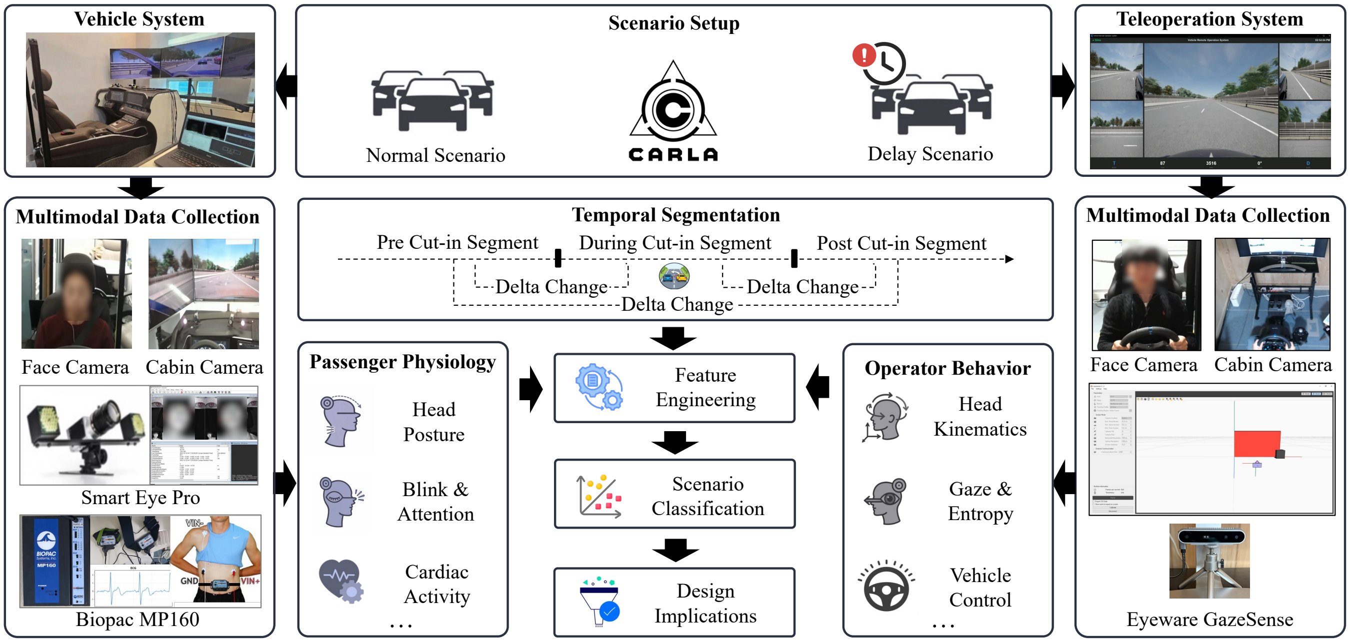

Figure 1: Overview of the experimental setup and analysis pipeline. Multimodal data from the passenger and remote operator is captured during Normal vs. Delay scenarios to classify network latency effects.

to capture holistic behavioral cues, including facial expressions and body posture. All data streams were time-stamped and fused to create a unified dataset of 102 valid experimental trials.

To effectively capture the dynamic and evolving nature of human responses to network delay, we implemented a feature engineering pipeline centered on temporal segmentation. Raw data from all modalities underwent preprocessing and synchronization, followed by aggregation into three distinct, event-aligned segments relative to the cut-in event: a Pre-event baseline (60s), the During-event period (8-10s) encompassing the critical maneuver, and a Post-event recovery phase (30s). From these segments, we extracted a comprehensive set of 1,422 features, encompassing standard statistical aggregates (mean, standard deviation, and entropy) for each segment. In addition, we computed "Delta features" as the change between segments ($\Delta_{\text{Pre-During}}$, $\Delta_{\text{Pre-Post}}$, and $\Delta_{\text{During-Post}}$), which were vital for quantifying the dynamics of response and capturing how behaviors and physiological states evolved from baseline, during the event, and into recovery. This temporally-aware feature set served as the input for our machine learning classification.

3.3 Classification and Feature Selection

To validate the predictive value of these multimodal features, we employed a machine learning pipeline centered on a Support Vector Machine (SVM) with an RBF kernel. Given the high dimensionality of our feature set, feature selection was critical to prevent overfitting and ensure transparency. To balance nonlinear discriminative power and interpretability, we employed a two-stage feature selection process within a 10-fold stratified, participant-wise (grouped) cross-validation scheme (participant ID as the grouping variable). First, a Random Forest (RF) classifier was used solely for feature ranking, capturing nonlinear effects and interaction dependencies that may not be detected by univariate statistical tests; features contributing to the top 90% of cumulative importance were retained. Second, an ANOVA F-test with a relaxed threshold ($p < 0.1$) was applied to the reduced feature set to retain statistically discriminative features, yielding a compact and interpretable subset for classification. This hierarchical approach reduced the input space to a compact subset of highly informative features. Within each fold, feature selection, median imputation, and standardization were fit on the training split only to prevent leakage. SVM hyperparameters were tuned via exhaustive grid search within the cross-validation procedure, and the final SVM model, optimized with $C = 2.0$ and $\gamma = 0.005$, served two purposes: achieving robust classification performance (demonstrating the detectability of the phenomena) and, more importantly, validating the key behavioral markers that differentiate Normal from Delay operations.

4 Results

The classification results confirm that network latency creates a detectable multimodal fingerprint across the entire operator-vehicle-passenger system. Our SVM model achieved a strong discriminative performance with an Area Under the Curve (AUC) of 0.8175 (±0.123) and an accuracy of 72.6% (±11.5%) in 10-fold cross-validation. While detection accuracy is valuable, the primary contribution of our analysis lies in the feature selection process, which isolated 81 key features (from the initial 1,422) that consistently differentiated between Normal and Delay conditions. These features clustered around distinct behavioral themes: driving behavior (37.0%), operator/passenger eye-tracking (42.0%), video-based behavioral indicators (19.8%), and physiological stress markers (1.2%).

Table 1: Comprehensive behavioral markers distinguishing Normal vs. Delay conditions. (Features selected via RF importance top 90% and ANOVA $p < 0.1$).

Behavioral Symptom	Metric / Feature	Normal	Delay	p
Operator Perception–Control Breakdown	Gaze Dispersion $\Delta_{\text{Pre-During}}$	-3.36	$+21.44$	.022
	High Steering Input %	55.20	75.80	$< .001$
	Lane Invasion Count (Pre)	14.70	23.78	$< .001$
Operator Cognitive Reconfiguration	Gaze Dispersion $\Delta_{\text{Pre-Post}}$	$+11.70$	-21.64	.012
	Scanpath Vel. $\%\Delta_{\text{Pre-Post}}$	$+4.88$	-6.99	.024
	Horizontal Gaze Entropy $\%\Delta_{\text{Pre-Post}}$	$+10.46$	-4.47	.014
Passenger Trust Decay	HRV (pNN50) $\Delta_{\text{Pre-During}}$	$+7.18$	-1.21	.021
	Horizontal Gaze Std. (During)	0.12	0.18	$< .001$
	Horizontal Gaze Std. $\Delta_{\text{Pre-During}}$	0.001	0.047	$< .001$
Passenger Attentional Lock-in	Horizontal Gaze Std. $\%\Delta_{\text{During-Post}}$	$+41.62$	-6.52	$< .001$
	Head Heading Range $\Delta_{\text{During-Post}}$	$+2.44$	0.90	.028
	Blink Rate $\Delta_{\text{During-Post}}$	-0.12	$+0.37$	.043

This clustering allows us to decode the specific human impacts of latency. Table 1 highlights the most representative features from these clusters, providing statistical evidence for the four key symptoms described below.

4.1 Perception–Control Breakdown

Latency disrupted the operator's perception–action loop, producing a coupled breakdown in visual monitoring and control. In Delay trials, operators exhibited a marked increase in *Gaze Dispersion* from baseline to the cut-in event (*Gaze Dispersion* $\Delta_{\text{Pre-During}} = +21.44$ vs -3.36), indicating heightened perceptual uncertainty and a shift toward predictive scanning under temporally unreliable feedback. This uncertainty propagated directly into the control channel: Delay trials showed significantly more *High Steering Inputs* (75.8% vs 55.2%), reflecting over-correction behavior. Critically, degraded control was not limited to the cut-in maneuver itself; *Lane Invasion Count* was elevated even during the Pre-event baseline (23.78 vs 14.70), suggesting that latency destabilized closed-loop control throughout the session.

4.2 Cognitive Reconfiguration

Post-event analysis revealed a fundamental divergence in visual scanning strategies. While operators in Normal conditions increased their visual scanning to re-establish awareness (e.g., *Gaze Dispersion* $\Delta_{\text{Pre-Post}} = +11.70$, *Scanpath Vel.* $\%\Delta_{\text{Pre-Post}} = +4.88$, *Horizontal Gaze Entropy* $\%\Delta_{\text{Pre-Post}} = +10.46$), Delay operators exhibited a sharp *negative* shift across all metrics (e.g., *Gaze Dispersion* $\Delta_{\text{Pre-Post}} = -21.64$, *Scanpath Vel.* $\%\Delta_{\text{Pre-Post}} = -6.99$, *Horizontal Gaze Entropy* $\%\Delta_{\text{Pre-Post}} = -4.47$). This confirms a phenomenon of Cognitive Reconfiguration: rather than returning to baseline, operators abandoned flexible environmental scanning in favor of a rigid, "tunnel vision" strategy. This indicates that under the threat of latency, operators do not merely struggle to recover; they fundamentally alter their cognitive approach by simplifying and narrowing their visual exploration to manage cognitive load, potentially at the cost of broader situation awareness.

4.3 Trust Decay

The impact of network latency extended beyond the remote operator to the vehicle's occupants, manifesting as measurable physiological and behavioral stress *during* the hazard, which we interpret as an rapid decay of passenger trust. During Delay trials, passengers exhibited a significant drop from baseline in *HRV (pNN50)* ($\Delta_{\text{Pre-During}} = -1.21$ vs $+7.18$), signaling an acute stress response to the vehicle's erratic behavior. This anxiety was mirrored in visual attention instability: passengers showed higher *Horizontal Gaze Std.* during the hazard (0.18 vs 0.12), alongside an increase from baseline in *Horizontal Gaze Std.* ($\Delta_{\text{Pre-During}} \approx 0.047$ vs ≈ 0.001). Together, these markers suggest that latency-induced micro-instabilities are perceptible to passengers in real time, producing erosion of perceived safety and control.

4.4 Attentional Lock-in

Beyond acute stress, latency also altered how passengers recovered after the hazard. In Normal trials, passengers showed a rebound in visual exploration during the recovery phase, reflected by increased *Horizontal Gaze Std.* ($\%\Delta_{\text{During-Post}} = +41.62$). In contrast, Delay trials exhibited a suppressed or reversed recovery pattern ($\%\Delta_{\text{During-Post}} = -6.52$), suggesting an attentional narrowing even after the cut-in maneuver ended. This rigidity extended to head movements, with Delay trials showing reduced re-orientation compared to Normal (*Head Heading Range* $\Delta_{\text{During-Post}}$: +0.90 vs +2.44). Finally, blinking patterns also remained unstable into the recovery window: *Blink Rate* increased under Delay ($\Delta_{\text{During-Post}} = +0.37$) but decreased under Normal ($\Delta_{\text{During-Post}} = -0.12$), indicating a disrupted return to normal visual behavior. These markers point to an Attentional Lock-in effect in which passengers recover more rigidly with constrained visual exploration and head-movement variability after the event.

5 Discussion and Design Implications

Network latency exposes a critical weakness in current teleoperation paradigms: operators must compensate for delayed feedback while passengers directly experience the resulting instability and uncertainty. This motivates shifting latency compensation from the human to the interface through targeted, latency-aware support.

Based on our findings, we propose four design guidelines for latency-aware interfaces. First, interfaces should employ predictive displays that visualize the vehicle's projected path and short-horizon motion to help operators act on future states rather than delayed video. Second, to stabilize control under delay, we recommend intent-level interaction, where operators specify goals (e.g., "Change Lane") rather than continuous micro-steering that is highly sensitive to lag. Third, to counter post-event attentional narrowing, systems should provide event boundary visualization that makes stabilization legible (e.g., explicit cues when network quality and control have recovered), encouraging operators to resume broader monitoring. Finally, to restore passenger trust and support post-event recovery, in-cabin interfaces should provide explainable feedback that the vehicle is aware of the lag, is adapting safety margins, and has returned to a stable control state, helping reduce sustained anxiety and attentional lock-in.

6 Conclusion

This study demonstrates that the effects of network latency extend far beyond technical performance metrics, manifesting as a distinct multimodal fingerprint of human distress. By decoding these signals, from the operator's coupled perceptual uncertainty and control instability and rigid cognitive strategies to the passenger's physiological anxiety and attentional lock-in during recovery, we have shown that latency fundamentally alters the human-machine control loop. These findings challenge the industry to move beyond simply optimizing network speed toward optimizing experienced quality. We plan to conduct comparative user studies to verify if these interventions successfully prevent the onset of operator attentional narrowing and support passenger recovery while mitigating physiological stress under degraded network conditions. Finally, because teleoperation was performed by trained staff members, operator signatures may not generalize; we will replicate with a broader operator sample and model operator-specific effects.

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