Clustering Attentional Types in Conditional Automated Driving for Adaptive Take-Over Request Design

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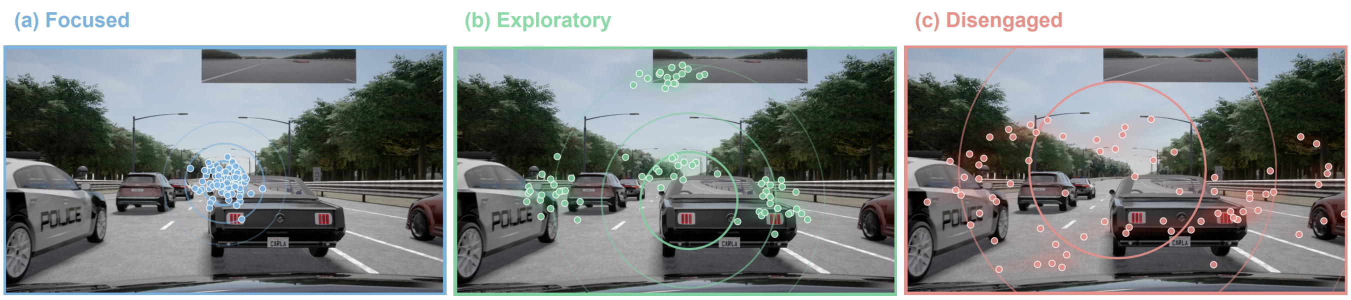

Figure 1: Gaze distribution overlays for the three attentional types in a photorealistic CARLA cut-in scenario. (a) The Focused type concentrates its gaze on the road ahead. (b) The Exploratory type actively scans the rearview mirror, adjacent vehicles, and the road ahead. (c) The Disengaged type scatters its gaze across off-road regions and the visual periphery. All three panels depict the identical driving scene.

Abstract

In SAE Level 3 conditional automated driving, a driver's attentional state before a Take-Over Request (TOR) critically shapes take-over quality, yet Driver Monitoring Systems rely on forward-gaze duration even though sustained forward gaze can coexist with mind-wandering. We applied K-Means clustering to 18 gaze and head-movement features from 93 drivers in a CARLA simulator and identified three attentional types: Focused, Exploratory, and Disengaged. The Focused type showed the highest forward-gaze ratio yet significantly lower situational awareness than the Exploratory type under high-demand conditions, a Forward Gaze Paradox that gaze-duration metrics cannot capture. The Disengaged type maintained near-ceiling physical readiness despite the lowest situational awareness, a cognitive-behavioral dissociation invisible to gaze-based monitoring. These types ground adaptive TOR interface design.

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CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**.

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1 Introduction

SAE Level 3 conditional automated driving permits Non-Driving Related Tasks (NDRTs) but requires rapid resumption of manual control upon a Take-Over Request (TOR) [SAE International 2021]. Prior TOR research has explored visual, auditory, and haptic feedback modalities [Gold et al. 2013] and gaze-attention methods [Patney et al. 2016] but has rarely modeled individual differences in pre-TOR attentional behavior, leaving open whether a single interface strategy suits behaviorally distinct drivers.

Two limitations motivate the present work. First, no established taxonomy links gaze monitoring variation to TOR response quality, despite documented behavioral differences among drivers [Kim et al. 2023]. Second, Driver Monitoring Systems (DMS) rely on forward-gaze duration, yet a driver may look forward while mind-wandering [Wickens 2008].

This study identifies attentional types from pre-TOR gaze and head-movement behavior and examines how each type relates to situational awareness and readiness. Multimodal gaze and head-movement features were extracted from 10-second pre-TOR intervals across 93 drivers and clustered via K-Means. Three contributions follow. First, the clustering reveals three demographically equivalent attentional types (Focused, Exploratory, and Disengaged) that reflect genuine behavioral variation (Figure 1). Second, the forward-gaze-awareness relationship is non-linear under high-demand conditions. Third, the Disengaged type shows a dissociation between physical and cognitive preparedness that forward-gaze-based DMS fails to detect.

2 Method

2.1 Experimental setup

A CARLA-based driving simulator equipped with eye-tracking and head-pose estimation systems served as the experimental platform. Three TOR scenarios were designed to span a range of situational demands. In the baseline scenario, the driver remained in automated driving mode until a TOR was issued, with no concurrent NDRT. In the cut-in scenario, a lead vehicle entered the ego lane while the driver performed a visual NDRT, which triggered a TOR. In the pedestrian-emergence scenario, a pedestrian unexpectedly entered the road while the driver performed a visual NDRT, triggering a TOR. Forward video, gaze coordinates, head orientation, and vehicle data were recorded synchronously across all scenarios.

2.2 Participants

Ninety-five licensed drivers were recruited for the study, and 93 who passed data-quality validation were retained for analysis. The final sample had a mean age of 37.0 years, with 48% female participants and a mean driving licensure duration of 2.4 years. Each participant completed an approximately 10-minute adaptation drive before the main trials, and the three scenarios were presented in randomized order per participant. This study was approved by the Institutional Review Board of the Electronics and Telecommunications Research Institute (2025-HR-0009).

2.3 Feature extraction and clustering

A 10-second pre-TOR window was extracted for each TOR event. Nine gaze features were derived, comprising fixation ratios over five screen regions (center, left, right, up, down), horizontal gaze variability, vertical gaze variability, overall gaze dispersion, and gaze validity. Nine head-movement features were derived, comprising standard deviation, range, and mean rate of change for the heading, pitch, and roll axes. Event-level features were aggregated to the driver level via the median to mitigate the influence of outliers. Features were normalized using z-score standardization, and K-Means clustering was applied. Clustering was repeated across multiple initialization conditions, and $K = 3$ was selected for interpretive coherence.

2.4 Subjective measures

Two questionnaires were administered after each scenario. Situational awareness was measured using the Situation Awareness Rating Technique (SART) [Taylor 1990]. Take-over readiness was assessed using a driver readiness scale adapted from prior TOR work [Zeeb et al. 2015]. Between-cluster differences were evaluated using one-way ANOVA when normality held and the Kruskal-Wallis H test otherwise. Effect size was reported as η^2. Post hoc comparisons were conducted using Mann-Whitney U tests with Bonferroni correction.

3 Results

3.1 Cluster definition and reliability

K-Means clustering yielded three interpretable attentional types (Table 1). The Focused type ($n = 39$) shows sustained forward-oriented attention. The Exploratory type ($n = 44$) shows active environmental monitoring through distributed gaze and head scanning. The Disengaged type ($n = 10$) shows frequent disengagement from the forward driving scene with low gaze validity and elevated postural instability.

The three-type structure proved robust across 10 independent initialization runs (> 95% assignment consistency excluding borderline cases). The types showed no significant demographic differences on age ($p = .307$), gender ($p = .736$), driving experience ($p = .108$), annual mileage ($p = .794$), traffic-violation history ($p = .850$), or prior experience with automated driving ($p = .543$).

3.2 Forward Gaze Paradox

A significant between-cluster difference in SART total score emerged exclusively in the pedestrian-emergence scenario ($F = 4.19$, $p = .019$, $\eta^2 = .092$). Counter to expectation, the Focused type recorded lower situational awareness ($M = 21.51$, $SD = 7.8$) than the Exploratory type, which scored highest ($M = 26.21$, $SD = 6.2$; post hoc $U = 498$, $p = .006$, $r = .308$). No significant differences appeared in the baseline or cut-in scenarios, indicating that the reversed awareness pattern emerges selectively under high-demand conditions. Subscale analysis reinforced the dissociation. The Exploratory type scored highest on the Understanding of Situation (UOS) subscale (trend in baseline, $p = .053$), and the Focused type scored highest on Demand on Attentional Resources (DAR; $M = 11.19$ compared with $M = 9.10$), indicating effortful yet inefficient attentional processing.

3.3 Cognitive-behavioral dissociation in the Disengaged type

The Disengaged type returned near-ceiling driver readiness scores across all three scenarios, with baseline $M = 9.62$ ($SD = 1.06$), cut-in $M = 9.88$ ($SD = 0.35$), and pedestrian emergence $M = 9.75$ ($SD = 0.46$). The between-cluster difference reached significance in the cut-in scenario ($p = .015$, $\eta^2 = .055$). The narrow standard deviations reflect nearly uniform hand-on-wheel behavior throughout the experiment.

The same type that maintained near-ceiling physical readiness also produced the lowest SART scores and the highest off-road gaze ratio. The dissociation replicated across all three scenarios, showing that physical-readiness indicators alone cannot reveal actual

Table 1: Attentional type profiles. Values are mean ± SD.

Feature	Focused (*n*=39)	Exploratory (*n*=44)	Disengaged (*n*=10)
Gaze validity	0.93 ± 0.05	0.85 ± 0.13	0.41 ± 0.25
Forward fixation ratio	0.78 ± 0.17	0.72 ± 0.22	0.25 ± 0.20
Off-road gaze ratio	0.04 ± 0.06	0.05 ± 0.07	0.40 ± 0.20
Head heading SD (°)	0.27 ± 0.18	1.07 ± 0.41	1.10 ± 0.52
Head roll SD (°)	0.009 ± 0.005	0.021 ± 0.016	0.031 ± 0.014

cognitive engagement. Figure 2(a) presents normalized profiles of all three attentional types across six gaze and head-movement features, and Figure 2(b) highlights the Disengaged type's consistently elevated driver readiness across scenarios despite low situational awareness.

4 Conclusion and Future Work

By clustering 93 drivers on pre-TOR gaze and head-movement behavior, this study identified three attentional types, demonstrating that current gaze-based driver monitoring oversimplifies attentional diversity. Forward-gaze duration alone does not guarantee situational awareness, and physical readiness can mask cognitive disengagement.

The findings motivate type-specific feedback: peripheral cues via Head-Up Display (HUD) or spatial audio for Focused drivers, concise forward-converging cues for Exploratory drivers, and multimodal escalation conveying situational information for Disengaged drivers, each pending validation in follow-up experiments.

Given the small Disengaged sample size and the simulator setting, future work will validate the attentional-type taxonomy in controlled real-vehicle experiments with prescreened participants spanning each type.

Acknowledgments

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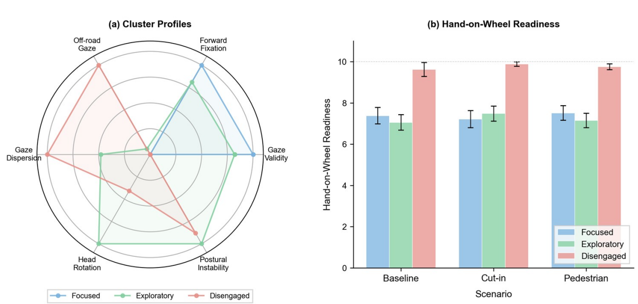

Figure 2: Cross-validation of the three attentional types. (a) Normalized cluster profiles across six key gaze and head-movement features. (b) Driver readiness across the three scenarios; the Disengaged type reports near-ceiling values consistently across all conditions.

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