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A Vision-Based Framework for Detecting Overtakes and Quantifying Novice Driver Responses in Continuous Simulator Traffic

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ABSTRACT

Novice drivers struggle to anticipate and respond to unexpected aggressive maneuvers by surrounding traffic. Most simulator studies use isolated, scripted hazards, which do not capture overtakes that emerge unpredictably in continuous traffic. This study developed a computer-vision framework to identify overtaking events in driving-simulator recordings and examine driver behavior during each event. Eighteen drivers with less than three years of U.S. licensure completed 144 trials under non-overtaking and overtaking traffic conditions. Overtakes were not scripted, and their timing, location, and frequency varied across trials. YOLO11× and motion-based ByteTrack were used to detect vehicles and overtaking events by tracking their movement. Overtaking events were manually reviewed and synchronized with driving logs recorded at approximately 30 Hz. Sixteen trials were used to calibrate the detection framework. On the remaining 128 held-out trials, the framework achieved 94.97% precision, 78.70% recall, and an $F1 = .861$. Drivers' behavioral analyses showed that in the overtake condition, mean speed was 8.26 mph lower and time above 45 mph was 40.00 percentage points lower than in the non-overtake condition. The framework provides an event-level method for studying traffic interactions in continuous simulator data and connects those events with measurable driver behavioral responses.

Keywords: Novice drivers, Human–automated vehicle interaction, Driver behavior, Overtaking maneuvers, Traffic safety

INTRODUCTION

Novice drivers face elevated crash risk during the early period of independent driving. Drivers with less than three years of independent driving experience are commonly classified as novice drivers (Wang et al., 2016; Robbins and Chapman, 2019; Xiang et al., 2024). In a naturalistic study of newly licensed drivers, crash and near-crash rates were higher during the first six months of licensure than during the following 12 months (Lee et al., 2011). Crash analyses indicate that inexperience contributes to this risk through several aspects of driving performance. Most crashes involving novice drivers were associated with errors in attention, visual search, speed relative to conditions, hazard recognition, and emergency maneuvering (McKnight and McKnight, 2003; Robbins and Chapman, 2019). Evidence from 16,914 newly licensed

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drivers also showed that vehicle-control performance at licensure predicted subsequent police-reported crash risk (Walshe et al., 2023). Experienced drivers are better at predicting hazards than novice drivers, particularly when the cues preceding a hazard were less obvious (Crundall, 2016). An aggressive overtake is therefore a useful event for human-factors study because another road user determines when the interaction begins, how quickly it develops, and when the novice must adjust.

This vulnerability is increasingly relevant as novice drivers enter mixed-traffic environments. In mixed traffic, autonomous vehicles (AVs) and human-driven vehicles (HVs) share the same roadway. Car-following experiments found differences in human-driver behavior behind AVs and HVs (Rahmati et al., 2019). Field and naturalistic analyses reported lower speed and acceleration volatility and higher time-to-collision values behind AVs, while the naturalistic data also showed shorter time headways (Mahdinia et al., 2021; Wen et al., 2022). Drivers have also accepted smaller gaps around AVs and returned closer after overtaking an AV than after overtaking an HV (Soni et al., 2022). These responses vary with AV driving style and recognizability, type of interactions, traffic composition, and the human driver's own driving style (Stange et al., 2022; Ma and Zhang, 2024; Saljoqi et al., 2026; Chen et al., 2026).

Human–AV interaction research has largely focused on drivers supervising in-vehicle automation and responding to takeover requests (Weaver and DeLucia, 2022). Comparatively few experiments have examined a novice driver in a surrounding HV who must interpret an AV maneuver while continuing to control the vehicle (Stange et al., 2022; Ma and Zhang, 2024). Existing studies of surrounding drivers have mainly examined car following, gap acceptance, overtaking an AV, and turning or yielding decisions (Mahdinia et al., 2021; Soni et al., 2022; Ma and Zhang, 2024). When an AV overtakes the participant, the participant does not choose when the AV approaches, how quickly it becomes adjacent, or when it moves ahead. The novice driver must interpret the maneuver while maintaining control of their vehicle.

In this study, the overtaking AVs were configured with higher desired speed and acceleration, shorter following headway, and more assertive lane-changing behavior. Existing studies have examined risk during overtakes initiated by human drivers, human decisions to overtake in the presence of oncoming AVs, and the gap acceptance and spacing when drivers overtook AVs (Pan and Shen, 2022; Soni et al., 2022; Mohammad et al., 2024). Several controlled simulator studies use predefined scenarios and vehicle behaviors to generate reproducible overtaking interactions (Pan and Shen, 2022; He et al., 2023; Mohammad et al., 2024). In the current study, overtakes are embedded within continuous traffic. In continuous traffic, the timing, location, and number of overtakes depend on the evolving positions and speeds of the ego vehicle and surrounding traffic. Here, the AV initiates the maneuver: it approaches from behind or beside the participant, becomes laterally aligned in an adjacent lane, and moves fully ahead. Recent computer-vision studies have approached overtaking and close-pass identification through scene- or vehicle-level recognition (Li et al., 2025) or by combining detection, tracking, and event rules to identify completed overtakes (Guo

et al., 2026; Padmanaban et al., 2026). Both approaches still require criteria that identify the responsible vehicle and mark the event boundaries.

Much of the previous work examines a predetermined interaction or averages behavior across an entire trial. Those designs do not answer a narrower question: what does the novice driver do when an aggressively configured AV overtakes the ego vehicle? This study first identified each overtake and then examined novice-driver behavior during the maneuver. We developed and evaluated an event-level framework that combined YOLO11× detection, ByteTrack tracking, deterministic event rules, and manual verification to identify overtaking events from simulator video. We synchronized the verified event boundaries with vehicle control data and compared novice-driver behavior between straight-road samples from non-overtake and overtake conditions. This study addressed the following research question: How does novice-driver behavior differ between the non-overtake and overtake conditions?

METHOD

The study was approved by the University of Louisville Institutional Review Board (IRB no. 25.0298).

Experiment procedure. Eighteen novice drivers (M age = 27.5 years, SD = 5.2; 13 men and 5 women) participated. Eligibility required obtaining a U.S. driver's license within the previous three years. After providing informed consent, participants completed a briefing and practice drive. They then completed eight experimental trials on a fixed route containing straight, curved, and merging segments. Participants were instructed about the 45-mph speed limit. Screen recordings were collected at 3840 × 720 pixels and 20 frames/s, and driving logs were recorded at approximately 30 Hz.

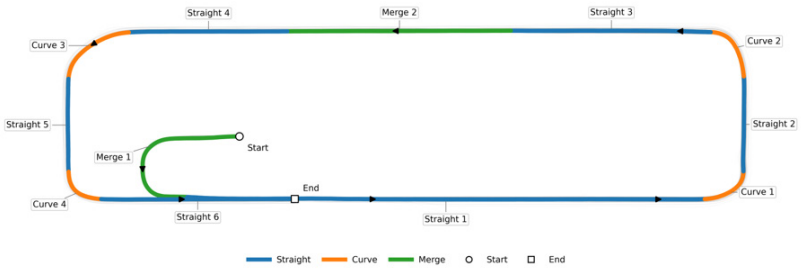


Figure 1: Road segments.

The route contained straight, curved, and merging segments as shown in *Figure 1*. Only straight-road segments were included in the analysis, and 16 participants had complete data across both conditions on these segments.

Experiment design. The study used a within-subject, repeated-measures design. The eight trials were divided among four session types, with two trials completed in each session. Sessions 1 and 3 used non-aggressive surrounding traffic and formed the non-overtake condition. Sessions 2 and 4 used aggressively configured AVs and formed the overtake condition.

Trial order was counterbalanced across participants to reduce order and carryover effects. The behavioral analysis compared two repeated conditions: non-overtake and overtake. Non-overtake driving was obtained from straight-road segments of Sessions 1 and 3. Overtake observations were obtained from qualifying AV overtakes in Sessions 2 and 4 in straight-road segments. The behavioral measures were mean speed, percentage of time above the instructed 45-mph speed limit, mean longitudinal acceleration, mean time headway, and mean headway distance. Mean throttle input was retained as a control-input measure. Speed was recorded in miles per hour, longitudinal acceleration in m/s², headway distance in meters, time headway in seconds, and throttle on a normalized scale from 0 to 1.

Table 1: Traffic parameters.

Setting	Baseline HV / Non-Aggressive AV	Aggressive AV
Role and model	Blue HV: IDM; red AV: CACC	Red AV: CACC
Maximum speed	20.12 m/s (45 mph)	23.14 m/s (51.75 mph)
Acceleration; time gap	2.6 m/s²; 1.0 s	4.0 m/s²; 0.5 s
Lane changing	Speed gain 1; pushy 0; assertive 1; right overtake 0	Speed gain 5; pushy 1; assertive 5; right overtake 1

Simulator traffic conditions. The experiment combined CARLA 0.9.15, an open urban-driving simulator (Dosovitskiy et al., 2017), with the SUMO microscopic traffic simulator (Alvarez Lopez et al., 2018). Each trial included 240 surrounding vehicles: 120 red AVs and 120 blue HVs. HV longitudinal behavior used the Intelligent Driver Model (IDM) (Treiber et al., 2000), and AV longitudinal behavior used cooperative adaptive cruise control (CACC) (Xiao et al., 2017). Table 1 summarizes the implemented parameters.

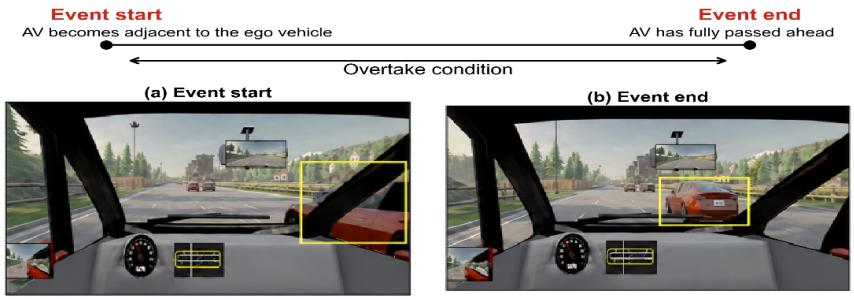


Figure 2: Overtaking-event window.

Vision-based event detection. An overtake event occurred when a surrounding AV approached from behind or beside the ego vehicle in the immediately adjacent left or right lane, became laterally level with the ego vehicle, and subsequently moved fully ahead as shown in *Figure 2* (Pan et al., 2025). A vehicle passing at high speed two or more lanes away did not qualify because it was never immediately adjacent. The framework had four stages (*Figure 3*).

First, YOLO11× detected vehicles in individual frames. Detection was restricted to the COCO car class and used an inference image size of 1600 pixels, a confidence threshold of 0.20, and an intersection-over-union threshold of 0.50. The relatively low confidence threshold helped preserve partially visible vehicles during rapid passes and transitions between display panels. Second, ByteTrack associated detections across consecutive frames. The tracker used motion-based association and retained both high- and low-confidence detections, which helped maintain a track when a vehicle was partly occluded or moving between display panels (Zhang et al., 2022). Appearance-based re-identification was disabled because many vehicles in the simulated fleet had similar appearances. Each valid vehicle track was required to contain at least eight frames. Third, hue-saturation-value rules classified red AVs and blue HVs. Classification required at least 25 matching pixels and a matching-color ratio of at least 0.015 within the tracked vehicle region. Lastly, deterministic spatial and temporal rules converted the tracks into overtaking-event candidates. The triple-monitor recording was divided into left, center, and right panels. In the recorded display, an overtaking vehicle first appeared in the left or right side panel and then moved into the center panel after passing the ego vehicle. Because distant vehicles 2–3 lanes away could also appear in a side panel, adjacency was determined from the tracked vehicle's bounding-box size and position. The height and area ratios measured the bounding box relative to the side-panel's height and area. Larger values generally indicated that the vehicle was closer. The inner-edge gap ratio measured the horizontal distance from the bounding box to the panel edge nearest the windshield, normalized by panel width; negative values indicated that the box extended into or beyond this inner-edge area. Under the strict rule, a vehicle was classified as adjacent when the inner-edge gap ratio was –0.30 or lower, or when the area ratio was at least 1.00 and the height ratio was at least 0.95. For tracks visible in a side panel for no more than 1.5 s, the relaxed rule used an inner-edge gap ratio of –0.24 or lower, or an area ratio of at least 0.85 combined with a height ratio of at least 0.85, to retain fast overtakes. All overtake events identified using either rule were manually reviewed.

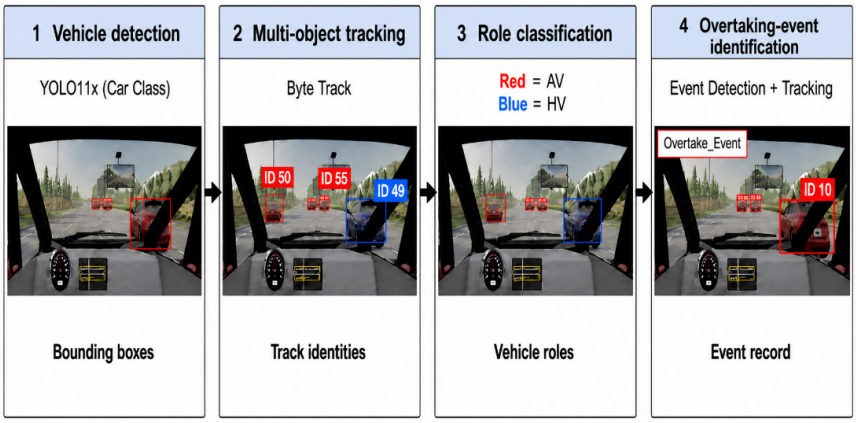


Figure 3: Vision-based overtaking detection framework.

Calibration and evaluation. The pipeline was calibrated on 16 random trials—one for each of 16 participants containing 10 verified overtakes. Thresholds were locked before the remaining 128 trials were evaluated. A reviewer recorded event onset, end, road geometry, side, and vehicle role and watched the full video for missed events. Matched events were true positives; unmatched detections were false positives; missed reference events were false negatives. Precision, recall, and *F*1 summarized complete-event detection. Frame-level metrics were not calculated because vehicle bounding boxes were not exhaustively annotated in every frame. Accuracy was omitted because continuous video has no natural true-negative count. Boundary corrections were also examined separately.

Behavioral measures and analysis. Behavioral measures were calculated from the final verified event set and the 144 driving logs. The aggressive sessions contained 103 overtakes beginning on straight segments. Two participants had no qualifying red-AV overtake beginning on a straight segment. Ninety-five overtaking events involved red AVs, and eight events involving blue HVs were excluded, leaving 95 events and 16 participants for analysis.

Statistical significance was evaluated at $\alpha = .05$. Paired-difference distributions were examined before hypothesis testing. Because of the small sample and normality violations in several outcomes, the two repeated conditions were compared using two-sided Wilcoxon signed-rank tests. Reported differences were calculated as overtake minus non-overtake. Holm's step-down procedure controlled the familywise error rate across all six behavioral outcomes (Holm, 1979), and matched-pairs rank-biserial correlation described contrast magnitude (Kerby, 2014).

RESULTS

Detection performance. Manual review identified 216 overtake events (211 in straight segments) in the 128 held-out evaluation set. The framework detected 179 events, of which 170 were true positives, and nine were false positives. Forty-six verified events were not detected. Event-level precision was 94.97%, recall was 78.70%, and the *F1*-score = .861 overall. Recall was 78.5% on straight segments, 78.3% on merges, and 76.7% on curves. For event temporal boundaries, among 170 matches, 167 onsets and 167 endpoints (98.24% each) were unchanged; both were unchanged for 164 events (96.47%). Mean absolute correction was .029s at onset and .018s at endpoint, with maxima of 2.00s and 1.00s.

Table 2: Participant-level behavioral outcomes by condition ($n = 16$).

Outcome	Non-Overtake, *M* (*SD*)	Overtake, *M* (*SD*)	Difference	*W*	Adjusted *p*	Rank-Biserial *r*
Mean speed (mph)	47.08 (4.15)	38.82 (6.52)	−8.26	0	< .001	−1.00
Time above 45 mph (%)	53.33 (20.49)	13.34 (15.70)	−40.00	3	< .001	−.96
Mean longitudinal acceleration (m/s^2)	0.18 (0.09)	−0.17 (1.72)	−0.35	56	1.000	−.18
Mean time headway (s)	5.39 (2.16)	4.97 (3.10)	−0.42	62	1.000	−.09
Mean headway distance (m)	113.73 (45.63)	83.47 (48.49)	−30.26	37	.350	−.46
Mean throttle input (0–1)	.65 (.03)	.62 (.07)	−.031	32	.262	−.53

Behavioral Responses Across Conditions. Table 2 presents the participant-level results for the non-overtake and overtake conditions. The clearest differences were observed for mean speed and percentage of time above 45 mph. Participants had significantly lower mean speed in the overtake condition ($M = 38.82$, $SD = 6.52$) than in the non-overtake condition ($M = 47.08$, $SD = 4.15$; Figure 4). Mean speed was 8.26 mph lower in the overtake condition than in the non-overtake condition (Holm-adjusted $p < .001$). Time above 45 mph was also significantly lower in the overtake condition ($M = 13.34\%$, $SD = 15.70$) than in the non-overtake condition ($M = 53.33\%$, $SD = 20.49$). Participants spent 40.00 percentage points less time above the speed limit during an overtake (Holm-adjusted $p < .001$). Mean longitudinal acceleration, mean time headway, mean headway distance, and mean throttle input did not differ significantly between conditions after Holm correction (*Table 2*).

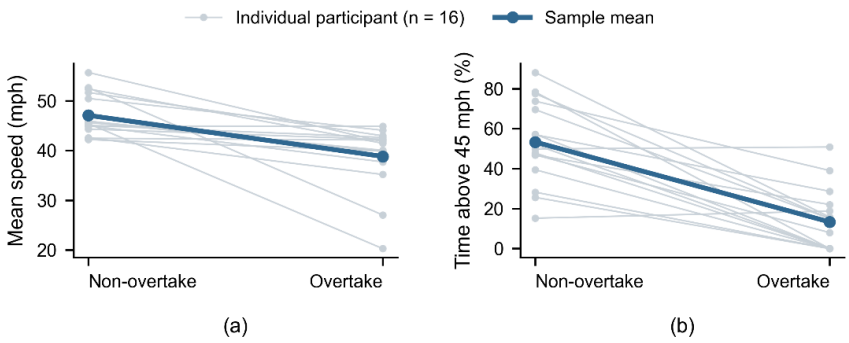


Figure 4: Speed-related outcomes in the non-overtake and overtake conditions: (a) participant-level mean speed and (b) time above 45 mph (%).

DISCUSSION

This study evaluated an event-level computer-vision framework to detect emergent overtaking maneuvers in continuous simulator traffic and examined novice-driver behavior during overtakes by aggressively configured AVs. The analysis showed a clear speed-related pattern: overtaking windows coincided with slower driving and less time above the instructed speed limit (45 mph). These findings extend earlier evidence that human drivers adjust their behavior around AVs (Rahmati et al., 2019; Mahdinia et al., 2021; Soni et al., 2022; Saljoqi et al., 2026). The present study adds the perspective of an ego vehicle being overtaken during an unscheduled interaction. However, the design cannot determine whether drivers slowed after noticing the approaching AV or whether lower ego-vehicle speed created the opportunity for the overtake. The findings therefore describe behavior associated with the maneuver without establishing that the AV caused it.

The vision-based event-identification framework addressed a practical measurement problem in continuous traffic. The traffic settings increased the opportunity for overtaking but did not determine exactly when or where an overtake would occur. Identifying the actual events provided a more direct measure of exposure than assigning all time within an aggressive session to the overtaking condition. Automated screening located overtake events, and manual review corrected their boundaries and recovered missed events. In our workflow, manual annotation required approximately 45 min per video on average. The combined workflow reduced average annotation time from approximately 45 to 15 min per video, including 5 min of video processing in Google Colab Pro using an A100 GPU. The process was not fully automated since it required manual verification. Automated screening missed some events and performed less consistently on curves. Changes in camera perspective and vehicle projection may have contributed. Further development should test the framework on curves, merges, and real-road recordings and improve its ability to identify events across changing road geometries.

Several limitations bound these findings. Novice status was based on U.S. licensure duration and may not capture experience gained elsewhere; no experienced-driver group was included. Larger studies should record total driving experience and compare diverse novice and experienced samples. Without an immediate pre-event window, the analysis cannot determine whether the speed pattern began before the AV became adjacent. The analysis included only AV overtakes beginning on straight segments, participants had unequal event exposure, and condition windows were not duration-matched. The AV configurations bundled vehicle role, appearance, control model, desired speed, acceleration, headway, and lane-changing settings. These factors cannot be separated in the present design. Future experiments should include a matched non-aggressive AV condition and vary these parameters independently. Surrounding-vehicle logs were not collected because of hardware constraints, so event-level relative speed, closing rate, and passing distance were unavailable. These data would have helped automate the overtake-detection process by providing direct information about surrounding vehicles' positions and movements. Future studies will

collect surrounding-vehicle logs and integrate them with video recordings to automate more of the event-identification and verification process.

CONCLUSION

This study developed an event-based framework combining computer-vision detection, manual verification, and synchronized driving data to examine novice-driver responses to aggressive AV overtakes. Locating each maneuver in continuous traffic accounted for differences in when and how often drivers were exposed. The study's broader contribution is an interaction-level view of automated driving: AV maneuvers should be evaluated together with the responses of nearby human drivers, especially novices managing unfamiliar traffic situations. This perspective may inform AV behavior design, driver-assistance systems, and event-based training that helps novice drivers recognize and respond to demanding interactions. The framework could also be adapted to examine cut-ins, merging conflicts, close following, and rapid lane changes. Human-centered AV evaluation should therefore consider whether mixed-traffic interactions remain predictable and manageable alongside conventional measures of maneuver completion and collision avoidance.

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