Behavioral and Physiological Responses to Takeovers in Different Scenarios during Conditionally Automated Driving

Na Du

Informatics and Networked Systems, University of Pittsburgh

Feng Zhou

Industrial and Manufacturing Systems Engineering, University of Michigan-Dearborn

Dawn M. Tilbury
College of Engineering, Robotics Department
University of Michigan

Lionel P. Robert
School of Information
College of Engineering, Robotics Department
University of Michigan

X. Jessie Yang
Industrial and Operations Engineering,
University of Michigan

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Corresponding author: Na Du, 135 N Bellefield Ave, Pittsburgh, PA 15213, Email: na.du@pitt.edu

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ABSTRACT

A variety of takeover scenarios will happen in conditionally automated driving. Previous studies presented mixed results regarding the effects of scenarios on takeover performance. According to drivers' strategies for takeover requests, this study selected eight representative takeover scenarios and categorized them into lane keeping and lane changing scenarios. To investigate the effects of scenario type and road environment (highway vs. urban) on drivers' takeover performance and physiological responses, a driving simulation study was conducted as a mixed design with 40 participants (average age = 22.8 years). The results showed that in lane changing scenarios, with the same sensing capability, drivers on highways had deteriorated takeover performance in the form of harsher takeover maneuvers and higher collision risk, as well as higher arousal and stress, compared to urban areas. However, such effects disappeared or even reversed in lane keeping scenarios on the curves, where drivers on highways had smoother takeover maneuvers and lower arousal and stress. These findings will help us understand the vital roles scenario type and road environment play during takeover transitions. Our findings have implications for the design of advanced driver-assistance systems and will improve driving safety in conditionally automated driving.

Keywords: Conditionally automated driving, takeover scenarios, road environment, takeover transition

1. INTRODUCTION

Automated driving promises to improve driving safety and fuel efficiency, and provide drivers with an opportunity to engage in non-driving-related tasks (NDRTs). However, SAE Level 3 automation requires drivers to resume control of the vehicle within a short period of time when the vehicle reaches its functional limit (Society of Automotive Engineers, 2018). As drivers are no longer required to monitor the environment actively, they may lose situational awareness and have difficulty taking over control of the vehicle when a takeover request (TOR) is issued (Ayoub, Zhou, Bao, & Yang, 2019; Du, Zhou, et al., 2020; Petersen, Robert, Yang, & Tilbury, 2019; Zhou, Yang, & de Winter, 2021; Zhou, Yang, & Zhang, 2019).

Researchers have investigated the impacts of different factors on drivers' takeover performance, such as driving environments (Gold, Körber, Lechner, & Bengler, 2016; Körber, Gold, Lechner, & Bengler, 2016; S. Li, Blythe, Guo, & Namdeo, 2018; Naujoks et al., 2017) and types of NDRTs (Du, Zhou, et al., 2020; Roche, Somieski, & Brandenburg, 2019; Wandtner, Schömig, & Schmidt, 2018; Yoon, Kim, & Ji, 2019). With regard to the driving environment, researchers have studied the effects of traffic density, road situations, and weather conditions on takeover performance. For example, research showed that heavy traffic density led to longer takeover time (Gold et al., 2016; Körber et al., 2016), more braking rather than steering (Eriksson & Stanton, 2017), lower minimum time to collision (Du, Kim, et al., 2020; Gold et al., 2016; Körber et al., 2016), more collisions (Gold et al., 2016; Körber et al., 2016), and larger maximum accelerations (Gold et al., 2016; Körber et al., 2016; S. Li et al., 2018). S. Li et al. (2018) found that city roads led to smaller resulting acceleration compared to highways and drivers in adverse weather conditions (i.e., snow, rain, and fog) had longer TOR response time, shorter minimum TTC, larger resulting acceleration, and steering wheel angle. Furthermore, Louw et al. (2017) found that less available visual information (i.e., fog) was linked to shorter minimum distance headway and minimum TTC. However, some of the above-mentioned studies used the same takeover scenario in the entire experiment (Gold et al., 2016; Hergeth, Lorenz, & Krems, 2017; Roche et al., 2019), not representing the wide range of takeover events that could happen in the real world. Takeover scenarios play a crucial role in shaping drivers' responses and warrant significant attention from researchers.

1.1 Takeover scenarios

Some studies designed a variety of takeover scenarios in order to examine their effects on takeover performance. For example, Naujoks, Mai, and Neukum (2014) examined effects of TOR modality (i.e., visual vs. visual plus auditory) under three takeover scenarios: missing lane markings, temporary lines because of a work zone, and high road curvature. Results of their study showed that drivers' lateral control was better with visual-auditory TORs, and such advantages were especially pronounced in the high road curvature scenario. Later, Naujoks et al. (2017) used the same three takeover scenarios and manipulated automation level (hands-on vs. hands-off vs. manual) and NDRT (with vs. without NDRT) in another experiment. They found that only in the temporary lines because of a work zone condition, engaging NDRT increased the self-reported situation criticality. Only in the high curvature scenario, high automation level increased variability of the lateral vehicle position and the self-reported situation criticality.

More recently, Dogan, Honnêt, Masfrand, and Guillaume (2019) investigated the effects of NDRTs on takeover performance in two takeover scenarios (i.e., missing lane markings and obstacles ahead). Results showed that regardless of NDRT type, drivers had shorter TOR response time and lower mental workload in the obstacle avoidance scenario than in the missing lane scenario. Similarly, Wu, Wu, Lyu, and Zheng (2019) analyzed drivers' takeover performance under different scenarios and NDRTs. Scenarios included obstacle on the left, obstacle ahead, and obstacle ahead with lead vehicle. NDRTs included a 1-back memory task and a letter game task. They found that drivers had the shortest steering response time in the obstacle ahead scenario, and longer minimum TTC in the obstacle ahead scenario than the obstacle ahead with lead vehicle scenario.

Treating different scenarios as distinct levels of the independent variable - takeover scenario - poses several challenges. Firstly, it becomes challenging to compare and reconcile the findings across different scenarios. Secondly, the generalization and scalability of the results may be limited.

One way to address this is to categorize the scenarios first before investigating their effects. To our knowledge, only two studies presented below tried to extract underlying influential dimensions of takeover scenarios. Eriksson et al. (2018) attempted to categorize scenarios into lane changing and braking scenarios, corresponding to different augmented visual interfaces to support drivers in making a correct lane changing or braking reaction in takeover transitions. Although the study did not compare the two scenario types directly, it did emphasize the fundamental differences between the two types and used different augmented feedback to provide recommendations. Zeeb, Härtel, Buchner, and Schrauf (2017) designed two scenarios based on the types of takeover responses in a simulated driving study. In the longitudinal scenario, drivers were required to intervene with a cutting in and hard braking vehicle. In the lateral scenario, drivers were required to intervene with the drifting vehicle on the curve induced by a wind gust from the left side. They found the detrimental effects of increasing manual task load on response time and takeover quality in both scenarios, but the effects were more pronounced in the lateral scenario. High cognitive load deteriorated response time and takeover quality in the lateral maneuver, but not in the longitudinal maneuver. Notably, researchers excluded 10 drivers who reacted with a lane change in the longitudinal scenario from analysis because their behavior was not comparable to the other drivers' reactions. However, it is common for drivers to brake and change lanes simultaneously in critical situations. This suggests that a better categorization of takeover scenarios is needed in order to study their effects.

1.2. Takeover responses

Regarding takeover responses, existing literature mainly focused on drivers' driving behaviors to quantify their responses during takeover transitions (Cao et al., 2021; Dogan et al., 2019) to understand and model the driver's takeover process. For instance, J. W. Kim and Yang (2020) employed various takeover performance indicators, including maximum acceleration, steering reversal rate, and standard deviation lateral position, to evaluate the effectiveness of different takeover alarm methods. Furthermore, Cao et al. (2021) conducted a comprehensive review of the research on takeover performance and proposed standardized metrics for measuring takeover performance in conditionally automated driving. While these indexes could help determine how efficiently and safely drivers can take over control of their vehicles, it is also important to know drivers' cognitive and emotional states in responses to takeovers, which can be reflected by their physiological responses.

Common metrics and measurement methods of physiological responses include eye movement (Huang, Yang, & Nakano, 2023), heart rate (HR) (Alrefaie, Summerskill, & Jackon, 2019), galvanic skin responses (GSRs) (Radhakrishnan et al., 2022), and electroencephalography (EEG) (Pakdamanian et al., 2020). For example, Du, Yang, and Zhou (2020) found that shorter TOR lead time led to inhibited blink numbers and larger maximum and mean GSR phasic activation, whilst heavy traffic density resulted in increased HR acceleration patterns than light traffic density. By examining these responses, researchers can better understand the underlying cognitive processes and emotional states experienced by drivers during the takeover process.

1.3. The present study

Existing studies that focused on takeover scenarios either directly treated various scenarios as the independent variable, resulting in the lack of generalization (Dogan et al., 2019; Naujoks et al., 2017), or categorized different scenarios into braking or changing-lane types, which overlooked the fact that it is common for a driver to brake and change lane simultaneously (Zeeb et al., 2017). A better categorization of takeover scenarios is needed in order to study their effects. Meanwhile, existing literature mainly studied a single factor such as TOR lead time from the road environment in understanding drivers' driving behaviors. In real-world scenarios, road features like curve radius and speed are highly correlated and should be investigated concurrently.

Our study aimed to investigate the effects of scenario type and road environment on drivers' takeover performance and physiological responses. Our contributions to the literature are outlined through several innovative aspects. First, we selected eight representative takeover scenarios and systematically categorized them depending on whether scenarios required drivers to change lanes or not (i.e., lane keeping vs. lane changing scenarios). As the lane keeping tasks have trivial consequences for non-takeover on the straight road, we chose to study the lane keeping scenarios on the curves which required takeovers to avoid deviation from the road. Second, we studied the effect of scenario type in different road environments (urban areas and highways). The unique characteristics of urban and highway settings, including different speed limits and layouts, presented an innovative approach to understanding how scenario types may interact with the road environment to shape drivers' takeover responses. Third, we incorporated physiological responses that can reflect cognitive and emotional states for a comprehensive assessment of drivers' responses during takeover transitions.

In the lane changing scenarios, drivers need to observe the driving environments and then change to available lanes to avoid the object ahead. With the same sensor range capability, highways with high vehicle speed indicate short TOR lead time defined as critical event onset for failures (McDonald et al., 2019). The visible objects ahead on highways may trigger quicker takeover responses, worsen drivers' takeover quality, and produce less desirable physiological responses. Thus, we proposed the first hypothesis:

H1: In lane changing scenarios, compared to urban areas, drivers on highways would have **(a)** shorter takeover response time; **(b)** harsher takeover behaviors reflected by maximum resulting acceleration/jerk and standard error (SE) of steering angle; **(c)** higher collision risk measured by minimum TTC; **(d)** more narrow attention allocation reflected by horizontal gaze dispersion; and **(e)** higher arousal and stress indicated by phasic GSR.

In the lane keeping scenarios, drivers need to apply pedals and steering wheel to maintain the vehicle in the current lane. To ensure safe and controlled driving on curvy roads, we assume that the vehicle (mass m) has the same centripetal force (F) no matter whether it is on the highway or urban curves. According to the equation $F = mv^2/r = mw^2r$, although the vehicle has higher speed (v) on the highway curves, its angular speed (w) is lower because the highway radius (r) is larger (Camacho-Torregrosa, Pérez-Zuriaga, Campoy-Ungría, & García-García, 2013; Porter, Donnell, & Mason, 2012). Lower angular speed may lead to slower takeover responses, better takeover quality, and trigger more desirable physiological responses.

Hence, we proposed the second hypothesis:

H2: In lane keeping scenarios, compared to urban areas, drivers on highways would have **(a)** longer takeover response time; **(b)** smoother takeover behaviors reflected by maximum resulting acceleration/jerk and SE of steering angle; **(c)** better lane maintenance measured by SE of road offset; **(d)** wider attention allocation reflected by horizontal gaze dispersion; and **(e)** lower arousal and stress indicated by phasic GSR.

2. Method

This research complied with the American Psychological Association code of ethics and was approved by the Institutional Review Board at the University of Michigan. Informed consent was obtained from each participant.

2.1 Participants

According to a power analysis through G*Power 3.1 software (Faul, Erdfelder, Buchner, & Lang, 2009), a sample size of 36 was necessary to achieve a statistical power of 0.95, with an anticipated medium effect size of 0.5 and an alpha level of 0.05. Thus, we recruited 40 university students (average age = 22.8 years, SD = 3.9; 20 females and 20 males) with normal or corrected-to-normal vision (i.e., wore glasses or contacts) in the experiment. Participants were screened for valid US driver's license status. All participants were active drivers, with 20 driving less than 50 miles per week, 17 driving 50-100 miles per week, and 4 driving more than 100 miles per week.

Participants self-evaluated their susceptibility to motion sickness during recruitment and experienced a training session to ensure they were not susceptible to simulator sickness. The study lasted about 60 minutes, and each participant was compensated with $30 upon completion of the experiment. Participants were informed that they were free to withdraw from the study at any time.

2.2 Apparatus and Stimuli

The study was conducted in a fixed-base driving simulator from Realtime Technologies Inc. (RTI, Michigan). The virtual world was projected onto three front screens (16 feet away), one rear screen (12 feet away), and two side mirror displays. The simulated vehicle was controlled by a steering wheel and pedal system embedded in a Nisan Versa car model. The vehicle was programmed to simulate an SAE Level 3 automation, which handled the longitudinal and lateral control, navigation, and responded to traffic elements. Participants could press the button on the steering wheel to activate the automated mode, which was indicated by a green highlight on the dashboard. Once the AV reached its system limit, the take-over request, consisting of an auditory warning ("Takeover") and disappearance of green highlight on the dashboard, would be issued. Meanwhile, the automated mode would be deactivated automatically and simultaneously, requiring the driver to take control of the vehicle. The system did not rely on the perception of the human driver's input to be deactivated.

The NDRT was a visual 2-back memory task, adapted from the study of (Jaeggi, Buschkuehl, Jonides, & Perrig, 2008). The task was selected to simulate drivers' eyes-off-the-road and hands-off-the-wheel condition in SAE Level 3 automated driving mode. Each stimulus, consisting of three by three squares with human figures randomly in two squares, was presented for 500 ms in sequence with a 2500 ms interval. Participants were required to press the "Hit" button when the current stimulus was the same as the one presented 2 back before in the sequence and press the "Reject" button otherwise. The task was running on an 11.6-inch touch screen tablet mounted in the center console of the vehicle (See Figure 1a).

The simulator was equipped with the SmartEye four-camera eye-tracking system (Smart Eye, Sweden) that provided live head-pose, eye-blink, and gaze data. The system was able to capture user eye-movements accurately even when they wore eyeglasses. The sampling rate of the eye-tracking system was 120 Hz. We used the Shimmer3 GSR+ unit (Shimmer, MA, USA) to collect GSR data with a sampling rate of 128 Hz (Figure 1b).

(a) In-vehicle NDRT environment (b) Physiological sensors

Figure 1. Experimental settings.

2.3 Experimental Design

The experiment used a mixed design with scenario type as the between-subjects variable and road environment as the within-subjects variable. Two types of scenarios were designed on the basis of realistic situations and previous literature (Koo, Shin, Steinert, & Leifer, 2016; Lisetti & Nasoz, 2004; Miller & Ju, 2014; Rezvani et al., 2016; Uhrig et al., 2016; Zeeb, Buchner, & Schrauf, 2016), that is, lane keeping and lane changing scenarios (See Table 1 and Figure 2). Each participant went through two road environments: urban areas and highways, with detailed information shown in Table 2. We tried to minimize variance between urban and highway settings, keeping road type, lane width, event sensing capabilities, and traffic density the same to prevent confounding variables. Specifically, the AV was always in the right lane of a two-lane road prior to the TOR. We set the distance between the AV and obstacle/entrance of the curve as 100 meters when the TOR was issued according to the range of Velodyne lidar (Velodyne Lidar, California). There were about 15 oncoming vehicles per kilometer of traffic (Gold et al., 2016). However, urban and highway areas exhibited several key differences in road layout to ensure safe and controlled driving. Based on the literature (Fitzpatrick, 2003; Poe & Mason Jr, 1995; Porter et al., 2012; Tarris, Mason Jr, & Antonucci, 2000), we set a highway curve radius of 600 meters with a shoulder width of 3.4 meters and an urban curve radius of 300 meters without shoulders. The speed limit was 35 mph in the urban areas and 60 mph on the highway, leading to a TOR lead time of 6.39 seconds in urban areas and 3.73 seconds on highways. We will discuss how these differences led to varying results in Discussion Section.

TABLE 1: *Descriptions of takeover events*

Event	Scenario type	Scenario descriptions
Event 1	Lane keeping	Sensor error on the left curve
Event 2		Right curve with construction zone on left
Event 3		No lane markings on the left curve
Event 4		Sensor error on the right curve
Event 1	Lane changing	Stranded vehicle ahead
Event 2		Construction zone ahead
Event 3		Construction barrier ahead
Event 4		Police vehicle on shoulder

(a) Lane keeping scenarios (b) Lane changing scenarios

Figure 2. Top-down view of the scenarios in the experiment

TABLE 2: *Descriptions of road environments*

	Urban	Highway
Road type	Two-lane road	Two-lane road
Width of each lane	3.6 meters	3.6 meters
Event sensing capability	100 m	100 m
Traffic density	15 vehicles/kilometers	15 vehicles/kilometers
Curve radius	300 meters	600 meters
Shoulder	No shoulder	3.4 meters
Speed	35 mph = 15.65 m/s	60 mph = 26.8 m/s
TOR Lead time	100/15.65 = 6.39 s	100/26.8 = 3.73 s

Participants were randomly assigned to one of the scenario types. The order of the scenarios was counterbalanced among participants. While we were not able to present scenarios in random order due to the programming constraints in the driving simulator, the event order was counterbalanced by having half of the participants drive from Events 1 to 4, and the other half from Events 4 to 1 within the same scenario type.

2.4 Dependent Measures

We measured participants' NDRT accuracy, takeover performance, and physiological responses after TORs. Takeover performance consists of takeover timeliness (TOR response time) and takeover quality (maximum resulting acceleration and jerk, minimum time to collision, SE of steering angle and road offset) (Du, Zhou, et al., 2020; Engström, 2010; Feng et al., 2017). According to the literature (Cao et al., 2021; Q. Li et al., 2023; Weaver & DeLucia, 2022), these metrics are robust to estimate takeover performance regardless of road layout and speed. Drivers' physiological responses include their horizontal gaze dispersion and phasic GSR (Gold et al., 2016; Merat, Jamson, Lai, & Carsten, 2012; Reimer, Mehler, Coughlin, Roy, & Dusek, 2011; Wintersberger, Riener, Schartmüller, Frison, & Weigl, 2018).

TOR response time was calculated as the time between TOR and start of the maneuver. The start of the maneuver was defined as changes above 2° of the steering wheel angle and/or 10% of the brake pedal position (Gold et al., 2016). Following prior research (Du, Zhou, et al., 2020), we calculated driving variables that measured takeover quality within the time window between the TOR and the end of the takeover action. For the lane changing scenarios, the takeover action ended when the vehicle's center of gravity reached the boundary of the neighboring lane. For the lane keeping scenarios, the takeover action ended when the driver passed the exit point of the curve. However, participants were instructed to re-engage the vehicle as long as they thought the vehicle was able to drive on its own. Hence, the takeover action ended earlier if participants re-engaged the vehicle before they reached the end point. To infer the smoothness of the maneuver, we used maximum resulting acceleration/jerk and SE of steering wheel (Du, Zhou, et al., 2020; Hergeth et al., 2017; Okada, Sonoda, & Wada, 2019). We used SE of road offset to describe the dispersion of the lateral lane position and a larger value of road offset SE represented worse lane maintenance performance (H. J. Kim & Yang, 2017; Mok et al., 2015; Mok, Johns, Yang, & Ju, 2017; Naujoks, Purucker, Wiedemann, & Marberger, 2019). Time to collision (TTC) was defined as the time taken for two objects to collide if maintaining their present speeds and headings (Hayward, 1972). A larger value of minimum TTC represented lower collision risk. Five crashes happened in lane changing scenarios, four on the highways and one in the urban areas. Participants either hit the objects or changed lanes on the shoulder during the collision. Under such situations, minimum TTC was treated as "not applicable".

Consistent with existing literature (Du, Yang, & Zhou, 2020), we calculated physiological responses within the time window between the TOR and the time when drivers re-engaged the vehicle. Drivers' horizontal gaze dispersion was defined as the standard deviation of gaze heading and could indicate their attention allocation (Louw, Kountouriotis, Carsten, & Merat, 2015; Merat et al., 2012; Wang, Reimer, Dobres, & Mehler, 2014). GSR phasic components were extracted from raw GSR signals using the continuous decomposition analysis (CDA) via Ledalab in Matlab (Benedek & Kaernbach, 2010). We calculated mean GSR phasic activation to indicate drivers' arousal and stress in response to TORs (Wintersberger et al., 2018).

2.5 Experimental procedure

Upon arrival, participants signed an informed consent and filled out a demographic form. Experimenters attached two GSR electrodes to the participants' left foot. After the sensor calibration, participants received a 5-minute training session, where they practiced how to keep lanes, change lanes and engage the automated driving mode by pressing a button on the steering wheel. They were asked to comply with all the traffic laws (e.g., speed limit) when they drove manually. Next, they started the NDRT and encountered an unexpected takeover event. The takeover event was the scenario where the traffic lights at the intersection did not work and required the driver to observe the surroundings and drive manually. Participants were told to re-engage the AV once they thought they had negotiated the situation for the AV. By providing feedback and correcting participants' wrong responses, the experimenter made sure that all participants were sufficiently acclimatized with the simulator and the system after the training.

Next, participants completed two experimental drives, with each drive consisting of two 4-minute scenarios and lasting approximately 11 minutes in total. As shown in Figure 3, each drive began with the command to activate the automated driving mode. Then there was an NDRT phase where participants were asked to do a visual 2-back memory task. The participants were informed that there was no need to actively monitor the environment when the AV was in automated driving mode. Once a TOR was issued, participants were required to take over control of the vehicle immediately. They could hand back the control to the AV after they negotiated the driving situation for the AV. The whole experiment lasted about 50 minutes.

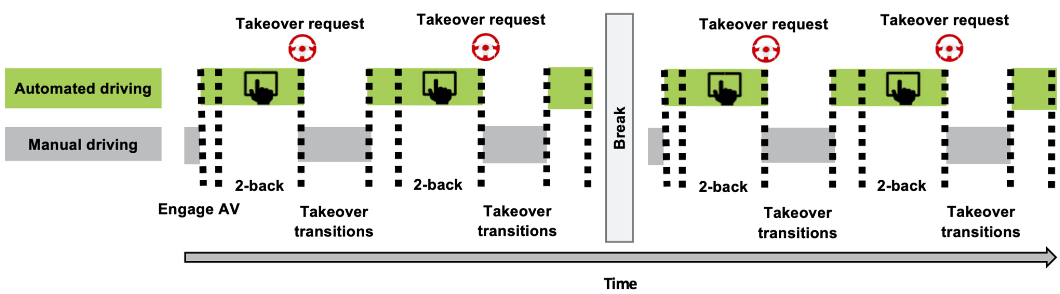


Figure 3. Sequence of takeover events in the experiment.

2.6 Data Analysis

Each participant experienced 4 events, resulting in 160 takeover events. Due to simulator and sensor malfunction, we excluded 9 events for driving behavior data analysis and 15 events for physiological data analysis. We used the linear mixed models to analyze the main effects of the road environment, scenario type, and their interaction effects on the dependent variables. The scenario type, road environment, and their two-way interactions were set as fixed effects. We used random intercept (participants had their own intercepts) but not random slope (participants did not have their own slopes) in the model development. α was set at .05 for results to be reported as significant. The individual-specific error terms were significant for all the dependent variables except minimum TTC.

3. RESULTS

Table 3 summarizes the mean and SE of objective takeover performance and physiological measurements. Within each scenario type, we did not find any significant differences among the four events on all the dependent variables, indicating the validity of the scenario categorization.

TABLE 3: *Mean and SE values of dependent measures*

	Lane keeping scenarios			Lane changing scenarios		
	Urban	Highways		Urban	Highways	
NDRT accuracy	0.90 ± 0.02	0.92 ± 0.02		0.85 ± 0.02	0.84 ± 0.02	
TOR response time (s)	2.87 ± 0.21	3.24 ± 0.28	support H2a	2.05 ± 0.09	1.78 ± 0.08	not support H1a
Resulting $acc_{\max}$ (m/s^2)	3.79 ± 0.27	2.70 ± 0.18		3.44 ± 0.53	6.56 ± 0.53	
Resulting $jerk_{\max}$ (m/s^3)	13.3 ± 3.9	10.2 ± 2.3	support H2b	76.2 ± 17.4	97.3 ± 17.3	support H1b
SE of steering angle (°)	0.56 ± 0.05	0.11 ± 0.01		0.33 ± 0.04	1.03 ± 0.13	
SE of road offset (cm)	0.89 ± 0.08	1.10 ± 0.16	not support H2c	2.41 ± 0.09	2.63 ± 0.12	
Time to collision$_{\min}$ (s)	NA	NA		1.63 ± 0.15	0.41 ± 0.10	support H1c
Horiz gaze disper (radian)	0.19 ± 0.01	0.15 ± 0.01	not support H2d	0.22 ± 0.01	0.21 ± 0.01	not support H1d
Mean phasic GSR (μS)	0.31 ± 0.06	0.21 ± 0.03	support H2e	0.29 ± 0.05	0.43 ± 0.07	support H1e

3.1 NDRT accuracy

Participants' average accuracy of 2-back memory task was 87.6% with a standard deviation of 8.4%, indicating strong engagement in the NDRT during automated driving. There were no occasions where participants took over before the takeover request was made. There was a significant main effect of scenario type on NDRT accuracy ($F(1, 38) = 9.85, p = .003, \eta_p^2 = .21$). Drivers had better NDRT accuracy before lane keeping scenarios than lane changing scenarios. No other significant effects were found.

3.2 Takeover performance

TOR response time. As shown in Figure 4, drivers reacted to takeover events sooner in lane changing scenarios ($F(1, 38) = 14.79, p < .001, \eta_p^2 = .28$). The interaction effect between scenario type and road environment ($F(1, 111) = 5.08, p = .026, \eta_p^2 = .04$) was significant. A simple effect analysis showed that, in lane keeping scenarios, drivers had shorter TOR response time in the urban areas than on highways ($p = .046$). No other significant effects were found.

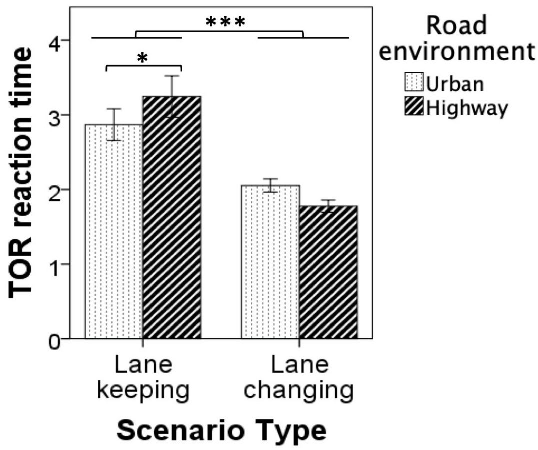
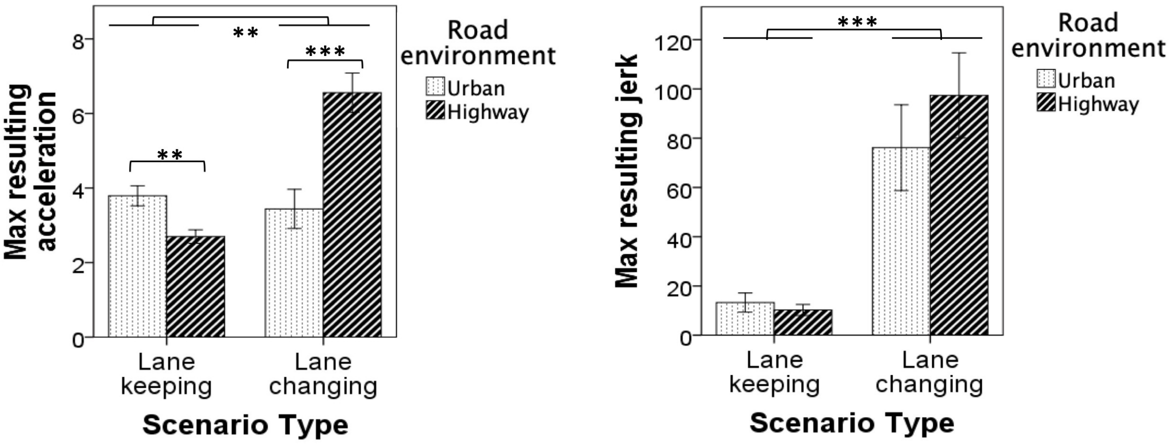


Figure 4. TOR response time (s) in different conditions. ***Difference is significant at the 0.001 level; **Difference is significant at the 0.01 level; *Difference is significant at the 0.05 level. Error bar indicates one standard error (The same for all the figures below).

Maximum resulting acceleration/jerk. There were significant main effects of scenario type ($F(1, 38) = 8.58, p = .006, \eta_p^2 = .18$) and road environment ($F(1, 110) = 15.49, p < .001, \eta_p^2 = .12$) on maximum resulting acceleration. Figure 5a shows that lane keeping scenarios and urban areas both led to a smaller maximum resulting acceleration. In addition, the interaction effect between scenario type and road environment ($F(1, 110) = 61.6, p < .001, \eta_p^2 = .36$) was significant. Drivers had larger maximum resulting acceleration in urban areas when scenarios were lane keeping ($p = .006$) but smaller maximum resulting acceleration in urban areas when scenarios were lane changing ($p < .001$). Regarding maximum resulting jerk, as shown in Figure 5b, only the main effect of scenario type was significant ($F(1, 38) = 16.14, p < .001$, $\eta_p^2 = .30$). Lane changing scenarios led to larger maximum resulting jerk compared to lane keeping scenarios.

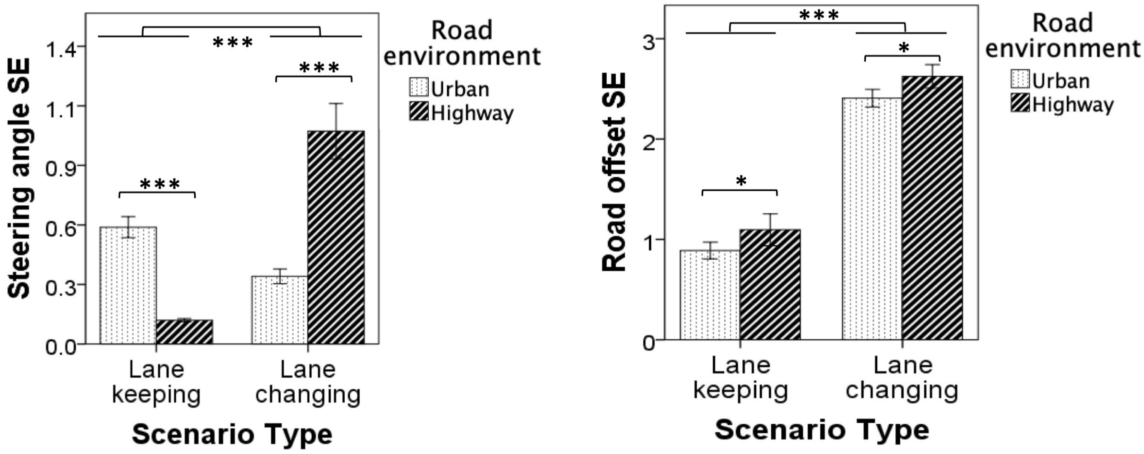


(a) Maximum resulting acceleration (m/s^2) (b) Maximum resulting jerk (m/s^3)

Figure 5. Driving smoothness

SE of steering angle. As shown in Figure 6a, the SE of steering angle in lane changing scenarios was larger than in lane keeping scenarios ($F(1, 32) = 22.49$, $p < .001, \eta_p^2 = .41$). The main effect of the road environment was not significant. Meanwhile, there was a significant interaction effect between scenario type and road environment ($F(1, 108) = 65.37, p < .001, \eta_p^2 = .38$). Drivers had a larger SE of steering angle in urban areas when scenarios were lane keeping ($p < .001$) but a smaller SE of steering angle in urban areas when scenarios were lane changing ($p < .001$).

SE of road offset. The main effects of scenario type ($F(1, 37) = 78.67$, $p < .001, \eta_p^2 = .68$) and road environment ($F(1, 110) = 4.98, p = .028, \eta_p^2 = .04$) were significant. As indicated in Figure 6b, drivers had a smaller SE of road offset in urban areas and lane keeping scenarios. However, their interaction effect was not significant.



(a) Standard error of steering angle (degree) (b) Road offset (centimeter)

Figure 6. Driving smoothness and lane maintenance

Minimum TTC. When the TOR was issued, the TTC was 3.73 seconds on highways and 6.39 seconds in urban areas. As shown in Figure 7, there was a significant main effect of road environment ($F(1, 54) = 62.27, p < .001, \eta_{\mathrm{p}}^2 = .54$) on minimum TTC in lane changing scenarios. The minimum time to collision was shorter on highways than in urban areas.

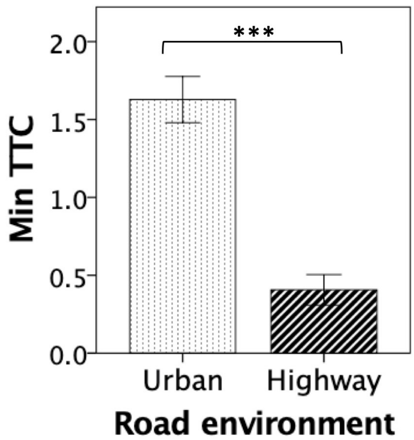
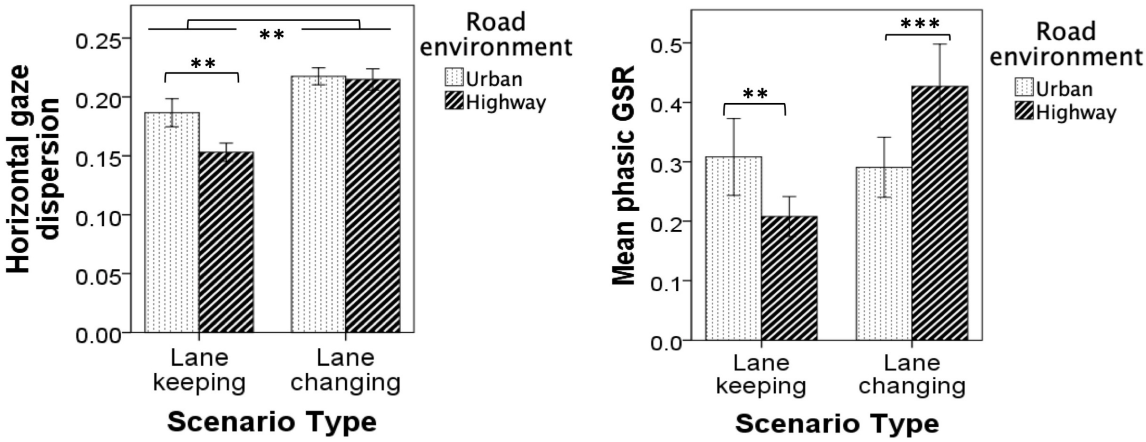


Figure 7. Minimum TTC (s) in different road environments.

3.3 Physiological measurements

Gaze behaviors. The main effects of scenario type ($F(1, 37) = 12.09$, $p = .001, \eta_{\mathrm{p}}^2 = .25$) and road environment ($F(1, 108) = 6.11, p = .015, \eta_{\mathrm{p}}^2 = .05$) on horizontal gaze dispersion were significant. In general, drivers had wider horizontal gaze dispersion in urban areas than on highways. Lane keeping scenarios led to narrower horizontal gaze dispersion than lane changing scenarios (Figure 8a). The interaction effect between scenario type and road environment on horizontal gaze dispersion was also significant ($F(1, 108) = 4.88, p = .029, \eta_{\mathrm{p}}^2 = .04$). Horizontal gaze dispersion was wider in urban areas in lane keeping scenarios ($p = .001$), but was similar regardless of road environment in lane changing scenarios (Figure 8a).



(a) Horizontal gaze dispersion (radian) (b) Mean GSR phasic activation (μS)

Figure 8. Physiological responses

GSRs. As shown in Figure 8b, there was only a significant interaction effect between scenario type and road environment on drivers' mean GSR phasic activation ($F(1, 106) = 25.24, p < .001, \eta_{\mathrm{p}}^2 = .19$). Compared to urban areas, drivers' mean GSR phasic activation on highways was significantly higher in lane changing scenarios ($p < .001$), but significantly lower in lane keeping scenarios ($p = .001$).

4. DISCUSSION

4.1 NDRT and Takeover performance

In conditionally automated driving, once the driver hears the TOR, s/he is expected to terminate the NDRT and use perceptual-motor calibration to take over control of the vehicle (Mole et al., 2019). In lane changing scenarios, the perception of the objects ahead triggers quick and reflexive motor behaviors such as hands/feet back on the wheel/pedals at a moment's notice. In lane keeping scenarios, however, curves are not as visible as the objects ahead and there are no other obvious contextual cues that require immediate motor control. This may be the main reason why drivers had better NDRT accuracy before lane keeping scenarios than lane changing scenarios.

We found that drivers' TOR response time was shorter in urban areas than on highways for lane keeping scenarios, but similar in both road environments for lane changing scenarios. The results supported **H2a**, which can possibly be explained by the geometric design of roads. Highway curves in lane keeping scenarios were not as curvy as urban curves (Aashto, 2001) and thus slowed down drivers' reaction of vehicle control at the time of TOR. Yet, **H1a** was not supported. This might be because the visible objects that appeared 100 meters away from the vehicle made the lane changing scenarios critical enough no matter where the AV was driving. Such urgent situations activated drivers' reflexive and equally quick takeover responses in both road environments.

Drivers' specific takeover actions differed depending on the scenario types. For the lane changing scenarios, drivers were supposed to check the neighboring lanes and then rotate the steering wheel to change lanes for object avoidance. Braking was necessary to reduce the distance from ahead objects to ensure safety distance and gain more time for decision making, while acceleration was necessary to facilitate the lane changing process. Yet, in the lane keeping scenarios, drivers just needed to focus on the current lane and adjust the steering wheel to maintain lanes on the curvy road, although brake and acceleration may be applied for better adjustment and vehicle dynamics.

Regarding driving smoothness, highways led to smoother maneuvers reflected by smaller maximum resulting acceleration and SE of steering angle in lane keeping scenarios, but harsher maneuvers represented by larger maximum resulting acceleration and SE of steering angle in lane changing scenarios. The results supported **H1b** and **H2b**. Since the distance between the AV and ahead objects/curve entrance was the same in all conditions at the time of TOR, highways with high speed limit indicated short TOR lead time. Our results aligned with the existing literature on the effects of TOR lead time on driving smoothness (Du, Kim, et al., 2020; Wan & Wu, 2018). In lane changing scenarios, highways engendered less time for lane changing behaviors and might lead to drivers' harsh usage of pedals and wheels to ensure safe distance to ahead objects and change lanes sharply (Gold, Happee, & Bengler, 2018). In lane keeping scenarios, although drivers had higher vehicle speed on the highway curves, their angular speed was lower compared to urban curves. With lower angular speed on highway curves, drivers adjusted pedals and steering wheel less frequently and maintained lanes more smoothly.

In lane changing scenarios, highways led to smaller minimum TTC, implying higher collision risk. In lane keeping scenarios, high speed led to larger SE of road offset, indicating worse lane maintenance performance. The results supported **H1c**, which was consistent with findings of previous studies (Du, Kim, et al., 2020; Roche & Brandenburg, 2019; Wan & Wu, 2018). Yet, the results did not support **H2c**. Although highway curves were less curvy and drivers controlled the vehicle more smoothly, drivers still had worse lane maintenance performance on highway curves. The possible explanation is that vehicle's deviation from the center of the lane on the curves was more related to vehicle speed rather than angular speed.

4.2 Physiological responses

Our results on drivers' horizontal gaze dispersion did not support **H1d** and **H2d**. In lane changing scenarios, drivers had similarly wide gaze dispersion in both road environments. This may be explained by their scanning strategies: drivers not only needed to look at the forward roadway, but also look around to check neighboring lane availability in lane changing scenarios. Such mechanisms may make the effects of the road environment negligible. Highways were associated with narrow horizontal gaze dispersion in lane keeping scenarios, suggesting limited monitoring span in rapidly dynamic environments (Engström, Johansson, & Östlund, 2005; Lemercier et al., 2014).

Compared to urban areas, drivers' had larger GSR phasic activation on highways in lane changing scenarios but smaller GSR phasic activation in lane keeping scenarios. The findings supported **H1e** and **H2e** and were aligned with previous studies (Du, Yang, & Zhou, 2020). As we described before, in lane changing scenarios, highways represented short TOR lead time and made scenarios more urgent. Thus, drivers had high arousal and stress on highways in lane changing scenarios. In contrast, highways were coupled with high speed, lower angular speed, and less curvy roads in lane keeping scenarios. As situations looked less critical, drivers had low arousal and stress on highways in lane keeping scenarios.

4.3 Limitations and implications

There are several limitations that should be taken into consideration in the future as research opportunities. First, as a simulated driving study, there was no real threat to driver safety and we were not able to randomly present scenarios due to the programming constraints. The effects of scenarios on takeover performance could differ in real-world settings. On-road testing with fake objects in the test facility can be conducted in the future to increase the ecological validity of results. Second, only young adults (university students) were recruited as participants. Future research can recruit participants with different individual characteristics such as age, driving frequency, and AV experience to explore potential variations in results. Thirdly, while we devised 8 takeover scenarios rooted in real-world tests and existing literature, and these scenarios align with common urban and highway situations, it is essential to acknowledge the existence of additional scenarios in daily driving. Moreover, urban and highway conditions can exhibit variations in curve radius, shoulder characteristics, lane length, and other factors. These variations may impact the generalizability of our findings. Future studies can enhance generalizability by incorporating a more extensive range of takeover scenarios, exploring additional variations in driving environments (e.g., higher speed conditions on highways), and systematically examining their effects.

The findings of this study can provide design implications for future advanced driver-assistance systems (ADASs). We recommend that ADASs should provide drivers with adaptive support according to scenario type and road environment. When the vehicle encounters a lane changing scenario on the highway or a lane keeping scenario on the urban curve, haptic shared control systems and collision warning systems can be initiated to smooth drivers' behaviors and reduce collision risk since such conditions lead to drivers' harsher takeover maneuvers and higher collision risk as proven by our study. In contrast, when the vehicle encounters a lane keeping scenario on the highway curve or a lane changing scenario in urban areas, drivers could exhibit good takeover performance based on our results. The ADAS can provide encouragement and make drivers confident of incoming maneuvers. Future research could investigate the content and format of the adaptive support in ADASs to enhance user experience and driving safety.

5. CONCLUSION

Our study selected eight representative takeover scenarios and categorized them into lane keeping and lane changing scenarios. We found that scenario type interacted with road environment to influence drivers' takeover performance and physiological responses to TORs. Our results showed that in lane changing scenarios, with the same sensing capability, drivers on highways had deteriorated takeover performance in the form of harsher takeover maneuvers and higher collision risk, as well as higher arousal and stress, compared to urban areas. However, such effects disappeared or even reversed in lane keeping scenarios on the curves, where drivers on highways had smoother takeover maneuvers and lower arousal and stress.

Our study is critical to understanding how scenario type and road environment influence drivers' takeover performance and physiological responses in conditionally automated driving. The findings of this study will add to the knowledge base on the role of different takeover scenarios in conditionally automated driving. It will help address safety concerns during takeover transitions and facilitate the adoption of automated vehicles.

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