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Effects of Non-Driving-Related Task Attributes on Takeover Quality in Automated Vehicles

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ABSTRACT

This study aimed to investigate the effects of non-driving-related tasks (NDRTs) on takeover quality in the context of automated driving. Specifically, we examined the effects of three categories of NDRT attributes (i.e., physical, cognitive, and visual) on longitudinal and lateral driving measures when the drivers resumed control. We designed a driving simulator study where the participants experienced automated driving journeys and takeover situations. When the automated mode was activated, drivers engaged in one of the nine NDRTs. The results showed that the cognitive load of NDRTs had a significant negative correlation with both longitudinal and lateral control measures. However, the effects of two attributes in the physical category and one attribute in the visual category on driving performance did not show statistical significance. Overall, the findings indicated that the influence of cognitive attributes on takeover quality is more salient than that of the physical and visual attributes, which provides insights into the understanding of takeover situations to improve driving safety.

1. Introduction

Automated vehicles are expected to play an important role in future transportation systems. However, the present automated driving systems cannot yet fully control a vehicle without driver intervention. According to the National Highway Traffic Safety Administration (2013), automated vehicles are classified into five levels (levels 0–4) depending on their automation performance. In all these levels, except for level 4, drivers need to be in the loop of driving tasks, even though automated driving systems can perform some of these tasks. However, given that drivers tend to engage in non-driving-related tasks (NDRTs) even when manually driving a car (Dingus et al., 2011; Horrey & Lesch, 2009), they are highly likely to be more distracted by NDRTs when driving vehicles in the automated mode (Jamson et al., 2013; Llaneras et al., 2013). Under such a condition, the risk of traffic accidents will be higher when the automated system fails. To investigate this issue, the effects of NDRTs on the takeover performance of drivers when the automated driving system fails have been researched (Bueno et al., 2016; Clark et al., 2017; Eriksson & Stanton, 2017; Favarò, 2020; Gold et al., 2016; Jeon, 2019; Kim & Yang, 2017; Naujoks et al., 2017; Petermeijer, Doubek et al., 2017; Roche et al., 2019; Wandtner et al., 2018; Yoon & Ji, 2019).

1.1. NDRTs in driving context

NDRTs are considered in two ways when investigating driver distraction in situations of traditional manual driving. First, standardized tasks requiring visual, auditory, manual, or cognitive loads can be used, such as a peripheral detection task (PDT), surrogate reference task (SuRT), or N-back task (Jahn et al., 2005; Jamson & Merat, 2005; Jeon et al., 2015; Niezgoda et al., 2015; Rodrick et al., 2013). The PDT method involves the presentation of visual stimuli that are required for drivers to detect targets when performing driving tasks (Harms & Patten, 2003). The SuRT method requires visual search and manual input similarly to that in the case of PDT, where the participants are asked to identify a circle shape target among the distractors (Petermeijer, Bazilinskyy et al., 2017). On the other hand, the N-back task artificially induces mental workload while performing a primary task (Owen et al., 2005). The advantage of these approaches is that they can easily manipulate the task demands or workloads, thereby precisely inducing the target state of the participants. However, the ecological validity of such tasks is low because they are not natural tasks being performed in real driving situations. Second, real tasks, such as searching for information, listening to music, calling, and texting, can also be used to induce a specific state (FakhrHosseini & Jeon, 2019; Favarò, 2020; Hancock et al., 2003; Jeong & Liu, 2019; Kim et al. 2019; Lee, Kim et al., 2019; Lee, Yoon et al., 2019; Mehler et al., 2016; Ogbanufe & Gerhart, 2018; Rumschlag et al., 2015). Although these approaches offer the advantage of conducting research more realistically and naturally, it is difficult to strictly control the level of task difficulty or workload.

Previous studies on driver behavior in the context of automated driving have also been conducted using both approaches (Bueno et al., 2016; Gold et al., 2018; Jarosch et al., 2017; Ko et al., 2019; Kutchek & Jeon, 2019; Naujoks

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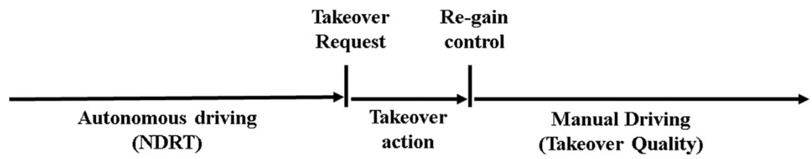

Figure 1. Takeover task procedure.

et al., 2019; Yoon & Ji, 2019; Zeeb et al., 2016). According to Ko and Ji (2018), for studying NDRTs, the concept of engagement and flow is more appropriate than the traditional workload-based paradigm in automated driving, which implies that natural tasks can be more effective than controlled artificial tasks. Therefore, in the present study, we used real NDRTs to observe the takeover behaviors of the driver when engaging in a realistic task.

1.2. Effects of NDRTs on takeover performance

The takeover time, which is the response time consumed to reengage control, is widely used to examine the takeover performance (Forster et al., 2017; Gold et al., 2016; Jeon, 2019; Ko & Ji, 2018; Kutchek & Jeon, 2019; Yoon & Ji, 2019; Yoon et al., 2019; Zeeb et al., 2015). One of the reasons many researchers have focused on this measure is that it enables them to observe the physical responsiveness of drivers to takeover events. However, the reflexive responses of drivers are not sufficient to measure the safety levels in takeover situations (Frison et al., 2019). This is because although drivers can reflexively respond to an emergent event, they cannot guarantee the situation awareness level for safely performing driving tasks. For example, Frison et al. (2019) showed that it is difficult for drivers to safely control the vehicle even though they are given 6 s. Therefore, to compensate for the time-based measures, driving-performance measures that have traditionally been used to evaluate the performance of manual driving, such as longitudinal and lateral control measures, were suggested to examine takeover quality after regaining the control of the car (Bueno et al., 2016; Favarò et al., 2019; Gold et al., 2016; Merat et al., 2014; Neubauer et al., 2012; Zeeb et al., 2015, 2016). Bueno et al. (2016) investigated the impact of different levels of mental workloads presented in NDRTs on takeover performances, including quality measures. According to the results, the takeover reaction time did not show a significant difference between low and high levels of demand. However, a significant difference was observed among the driving measures, time to collision, and maximum steering wheel angle to avoid the hazard. Gold et al. (2016) and Zeeb et al. (2015, 2016)) also reported that the engagement in NDRTs had a more significant impact on takeover quality as compared to that on takeover time. Merat et al. (2014) showed that drivers took ~40 s to maintain stable lateral control of the vehicle after resuming control, regardless of their physical responsiveness. Based on relevant literature, we conclude that takeover-quality measures can compensate for the weakness of takeover-time measures.

1.3. Present study

Although previous studies have been conducted on takeover performance, it is unclear how NDRTs affect the driving performance after drivers regain vehicle control. We aimed to investigate the effects of NDRTs on takeover quality using driving performance measures, after physically regaining the control. Specifically, we examined the effects of physical, visual, and cognitive attributes of NDRTs on driving-quality measures. We assumed that different NDRT attributes have different influences on takeover-quality measures. Specifically, we hypothesized that the influence of cognitive attributes on takeover-quality measures is more salient than those of physical and visual attributes, based on previous findings (Engström et al., 2005; Jamson & Merat, 2005; Zeeb et al., 2015). To achieve this research objective, a driving simulator experiment with automated driving journeys and NDRTs was designed and conducted. Data on longitudinal and lateral control measures were collected to analyze the takeover quality after reengaging control.

2. Method

2.1. Participants

Thirty participants (18 males and 12 females) between 25 and 39 years of age (mean = 28.9 years, *SD* = 4.20) participated in the experiment. All participants were required to have a valid driver's license and more than one year of driving experience (mean = 9.9 years, *SD* = 3.95). None of the participants had any visual or cognitive impairment that would affect their driving.

2.2. Experimental design

A driving simulator experiment was designed and conducted to investigate the takeover quality after regaining control, when the participants performed different NDRTs during the automated driving mode. Automation levels 2–3, based on the NHTSA automation level, were designed for the experiment, where the participants could experience full automation during a given period while they had to take over vehicle control due to the system request. In the experiment, the participants experienced autonomous driving, where they had to perform different NDRTs. A takeover request alert was given to regain vehicle control, where the driving performance of the participants was measured after regaining vehicle control. Thus, we explored the influence of NDRT attributes on takeover-quality measures (Figure 1).

2.3. NDRTs

The participants experienced automated driving journeys with 10 NDRTs: 1) conversing with a passenger, 2) listening to music, 3) talking on their phone (handheld), 4) watching a video from the center console, 5) reading a book, 6) texting with a smartphone, 7) operating the in-vehicle information system (IVIS), 8) playing games on the phone, 9) holding and drinking a beverage, and 10) without any NDRT. These 10 NDRTs were selected based on the tasks that have been used to induce different load levels on the drivers in the literature (Jeong & Liu, 2019; Naujoks et al., 2019; Yoon & Ji, 2019; Yoon et al., 2019). These NDRTs were also selected based on two physical attributes, two cognitive attributes, and one visual attribute (Table 1). The physical attributes refer to a driver's physical status when performing NDRTs, which affect their motor readiness when taking over vehicle control. The two physical attributes chosen were "place of interaction" and "hand in use." The cognitive attributes consider the resource aspects that might influence a driver's information analysis and decision-making while taking control. The two cognitive attributes selected were "resource utilization" and "cognitive load." The visual attribute chosen was "gaze location" while performing the NDRT.

However, we did not predefine the levels of each variable for the NDRTs, because they can differ depending on the participants. For example, the participants can naturally use a smartphone with one hand or both hands according to their preference. It might be possible to ask the participants to perform a task in a controlled position or posture; however, we were interested in obtaining natural data. Therefore, we predefined the levels of "place of interaction" and "resource allocation" for each task; however, we post-coded the levels of "hand in use" and "gaze location" based on the video recording of the experiment, as in the case of Clark et al. (2017). Additionally, we used subjective evaluations from the participants to determine the cognitive load. Table 1 summarizes the NDRT attributes, descriptions, and levels of each variable.

2.4. Takeover-quality measures

We selected quality aspects that describe the transition of control for longitudinal and lateral controls while driving manually, based on previous studies (Jarosch et al., 2017; Merat et al., 2014). For the longitudinal control, the mean longitudinal acceleration (MLONGA), maximum longitudinal deceleration (MAXLONGD), maximum velocity (MAXV), minimum velocity (MINV), distance to collision (DTC), and time to collision (TTC) were measured. For the lateral control, mean lateral acceleration (MLATA), maximum lateral acceleration (MAXLATA), and standard deviation of lane position (SDLP) were measured. Table 2 describes the dependent measures.

2.5. Apparatus

A driving simulator comprising a steering wheel, gas and brake pedals, a seat, a front driving monitor, and a tablet PC was used. The STISIM M100K driving simulator software was used to generate the driving scenarios, and the steering wheel and pedals were purchased from Logitech Racing Wheel G27. The driver's seat, with adjustable seat positions, was obtained from a Genesis model developed by Hyundai Motors. Driving scenes were presented on a 50-in Samsung TV. An Apple iPad Pro 12.9-in model was used as the center console display. Tobii Pro Glasses 2 and Tobii Pro Lab software were used to observe the glance behaviors. Figure 2 shows the experimental settings.

2.6. Procedure

The experiment details were explained to the participants, who then signed the consent form approved by the University's Institution of Review Board (IRB). The participants were first given a practice session to familiarize themselves with the driving simulator and automated driving. During this session, the participants were given several takeover tasks to help them understand the task process and manual driving after reengaging into the vehicle control. In the main session, the participants were asked to engage in one of the 10 NDRTs, which were provided randomly, before takeover requests were suggested. To prevent fatigue, the main experiment was divided into two sessions, and a short break was given in between the sessions. The driving scenarios comprised both manual and automated driving. The participants started with manual driving, and after driving for approximately 1.5 km, the automated driving mode was activated. The automated driving mode lasted for approximately 5 min, which is regarded as sufficient time to make drivers engage in NDRTs according to the literature (Körber et al.,

Table 1. Independent variables of NDRT.

NDRT attribute	Independent variable	Description	Level
Physical attribute	Place of interaction	The place where the NDRT is actually taking place	1 = handheld 2 = mounted 3 = none
	Hand in use	The hand being used for the NDRT	1 = one 2 = both 3 = none
Cognitive attribute	Resource allocation	The utilization of resources when performing the NDRT	1 = visual 2 = auditory 3 = visual + auditory 4 = auditory + verbal 5 = visual + auditory + verbal 6 = none
	Cognitive load	The degree of mental effort perceived by the participant	0–10 points score
Visual attribute	Gaze location	The gaze position when performing the NDRT	1 = center console 2 = right 3 = down 4 = front

Table 2. Longitudinal and lateral control variables for measuring takeover quality.

Takeover-quality variable		Description
Longitudinal Control	Mean longitudinal acceleration (MLONGA) [m/s^2]	Average acceleration and deceleration during manual driving
	Maximum longitudinal deceleration (MAXLONGD) [m/s^2]	Maximum deceleration after reengaging vehicle control
	Maximum velocity (MAXV) [km/h]	Maximum velocity reached by the vehicle during manual driving after reengaging control
	Minimum velocity (MINV) [km/h]	Minimum velocity reached by the vehicle during manual driving after reengaging control
	Distance to collision (DTC) [m]	Minimal distance to collision before changing lanes to avoid collision
	Time to collision (TTC) [s]	The remaining time from when the driver starts changing lanes to avoid collision, obtained by the remaining distance divided by the speed at that moment
Lateral Control	Mean lateral acceleration (MLATA) [m/s^2]	Absolute mean lateral acceleration during manual driving
	Maximum lateral acceleration (MAXLATA) [m/s^2]	Absolute maximum lateral maneuver of the steering wheel after the takeover request
	Standard deviation of lane position (SDLP) [m]	Variance in lateral position from the lane center during manual driving

Figure 2. Experimental settings.

2018; Naujoks et al., 2019; Roche et al., 2019; Yoon et al., 2019). Then, a takeover request was suggested when the car encountered a construction situation. The participants could reengage in vehicle control by pressing a button on the steering wheel, as an indication of readiness to drive. After driving for approximately 1.5 km, the automated driving mode was activated again. Once the automated mode was activated, the participants were asked to evaluate the cognitive load and cognitive engagement of the NDRT they previously performed. Data collection was performed immediately after each task repetition. All procedures took approximately 1 h.

2.7. Data collection and analysis

All dependent measures of takeover quality were automatically collected using the driving simulator software. To analyze the effects of physical attributes on takeover-quality measures, these data were transformed using the aligned rank transform (ART) method (Wobbrock et al., 2011), and then, the transformed data were analyzed by conducting a non-parametric equivalent of ANOVA. To evaluate the effect of NDRT gaze and cognitive attributes on takeover quality, the Kruskal-Wallis H was selected. All statistical analyses were conducted using the IBM SPSS Statistics 24 software.

3. Results

3.1. Effects of physical attributes of NDRTs

There were no significant effects of "place of interaction" and "hand in use" on all measures of longitudinal and lateral control, except for MLONGA (Table 3). The only significant difference was found in MLONGA, depending on the hand in use (F (2, 297) = 4.987, $p < .05$).

3.2. Effects of cognitive attributes of NDRTs

To evaluate the effects of cognitive attributes of NDRTs on takeover quality, two statistical analyses were conducted. First, a non-parametric Kruskal-Wallis H test was applied to evaluate the effect of resource allocation. Table 4 shows the results, demonstrating that only a significant main effect was found in MLONGA for longitudinal control. This effect can be further explained by Figure 3, where the least deceleration occurred during visual and verbal/auditory resource allocation, while the greatest deceleration occurred with visual/auditory NDRTs.

Additionally, a correlation analysis was conducted to investigate the relation between cognitive load and takeover-quality measures (Table 5). The results demonstrated that there were significant linear correlations between cognitive load and measurements of longitudinal and lateral control.

There was a significant positive correlation between MLONGA and the cognitive load of the participants, meaning that as the degree of cognitive load increased, the participants decelerated more. This was also shown by the significant negative correlation between MAXLONGD and the cognitive load (r = −0.114, $p < .05$). Two measures, DTC and TTC, also showed a significant negative correlation with the cognitive load, indicating that the remaining distance and time for drivers when avoiding a hazard were less for the participants with greater cognitive loads (Table 5).

For the lateral vehicle control, the results of a Pearson correlation analysis showed that increasing the degree of cognitive load had a significant positive correlation with MAXLATA (r = 0.122, $p < .05$) and SDLP in 5 s after reengaging control (r = 0.124, $p < .05$).

Table 3. Results of ANOVA for "place of interaction" and "hand in use" on takeover-quality measures.

		Physical Attribute			
		Place of interaction		*Hand in use*	
Takeover-quality measures		*F*	*p*	*F*	*p*
Long. Control	MLONGA	2.207	0.138	4.987*	0.026
	MAXLONGD	1.544	0.215	0.322	0.571
	MAXV	1.379	0.241	0.425	0.515
	MINV	0.097	0.756	0.056	0.813
	DTC	0.462	0.497	0.001	0.970
	TTC	0.000	0.995	0.043	0.836
Lat. Control	MLATA	1.161	0.282	0.256	0.613
	MAXLATA	2.499	0.115	0.025	0.875
	SDLP	0.941	0.333	1.053	0.306

*Note. *: p < 0.05*

Table 4. Results of cognitive resource allocation on takeover-quality measures.

		Resource allocation	
Takeover-quality measures		$\chi^2(5)$	*p*
Long. Control	MLONGA	12.128*	0.033
	MAXLONGD	5.342	0.376
	MAXV	9.456	0.092
	MINV	6.650	0.248
	DTC	4.085	0.537
	TTC	4.656	0.459
Lat. Control	MLATA	3.305	0.653
	MAXLATA	2.139	0.830
	SDLP	1.285	0.936

*Note. *: p < 0.05*

3.3. Effects of visual attributes of NDRTs

Significant effects of the visual attribute "gaze location" were found in only two longitudinal control measurements, while no significant main effects were found in lateral control measurements (Table 6).

Figure 4 demonstrates a significant effect of gaze location on MLONGA ($\chi^2(3)$ = 14.897, $p < .05$) and MAXV ($\chi^2(3)$ = 8.973, $p < .05$). The mean longitudinal acceleration for the four conditions was negative, indicating that all drivers decreased their speed. The greatest mean deceleration occurred when the NDRT required the participants to have their gaze on the center console, while the least mean deceleration occurred when drivers had their head positioned down (i.e., gaze on a smartphone or book). However, the maximum velocity results indicate that when the participants were required to gaze on the loop, their maximum velocity reached almost 100 km/h, but they had lower maximum velocities when looking at the center console or had their head positioned down.

Figure 3. Visual attribute effects on (a) mean longitudinal acceleration and (b) maximum velocity

4. Discussion and conclusion

In this study, we conducted a driving simulation experiment under the hypothesis that the effects of NDRT attributes on the driving performance after reengaging vehicle control would be different. We collected lateral and longitudinal driving measures during 10 natural NDRTs before a takeover situation in the driving simulator.

The resource allocation of NDRTs did not have a significant effect on takeover quality. Consistent with previous research, we can conclude that the resource allocation during the NDRT influences the timing aspects of the transitioning control of the vehicle. However, according to our findings, the modalities of NDRTs do not have a significant effect on driving quality once the transition process is complete. Roche et al. (2019) reported that the driver's SDLP after takeover was influenced by NDRT modality, which is contrary to the findings of this study. They examined both modalities of takeover request and NDRTs, which means their results can be attributed to the interaction effects of modalities.

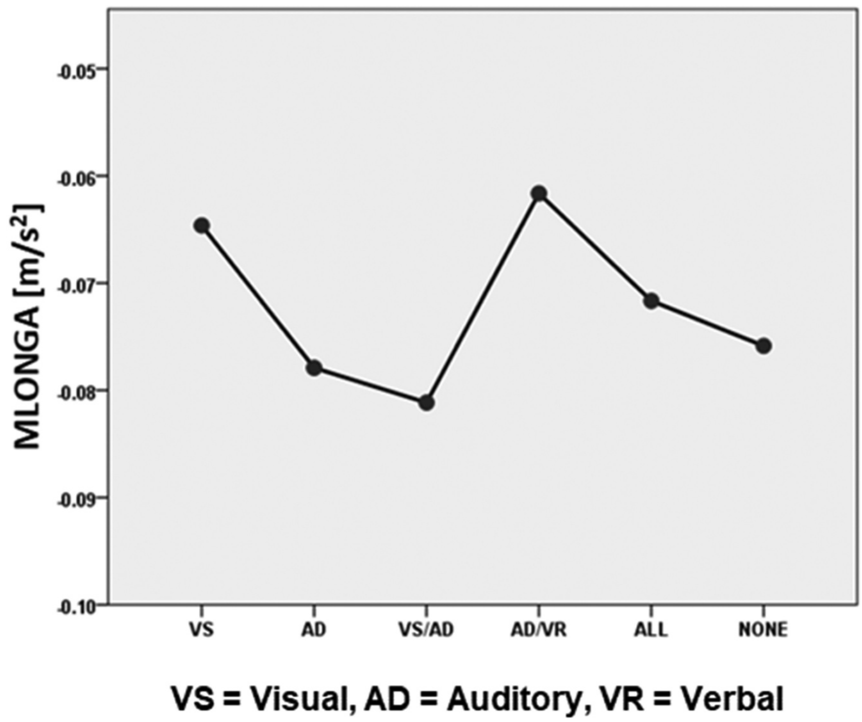

Figure 3. MLONGA for cognitive resource allocation.

The results demonstrate that the degree of cognitive load during NDRTs has a significant positive correlation with longitudinal and lateral controls during manual driving. Specifically, the maximum longitudinal deceleration had a positive correlation with the cognitive load, meaning that as the cognitive load of the NDRT increased, drivers decelerated more to avoid the hazard. Additionally, the distance to collision and time to collision were found to have a significant negative correlation with cognitive load, indicating that the minimum time and distance before changing lanes to avoid collision were shorter as the perceived cognitive load of the NDRT increased.

Table 5. Correlation analysis results for cognitive load and takeover-quality measures.

Takeover-quality measures		Cognitive load *r*	Cognitive load *p*
Long. Control	MLONGA	0.204**	< 0.001
	MAXLONGD	− 0.114*	0.05
	MAXV	0.097	0.094
	MINV	0.057	0.327
	DTC	− 0.148*	0.011
	TTC	− 0.142*	0.014
Lat. Control	MLATA	0.108	0.063
	MAXLATA	0.122*	0.036
	SDLP	0.036	0.532
	SDLP in 5 s.	0.124*	0.033

Note. *: $p < 0.05$, **: $p < 0.01$

Table 6. Results of the main effect of "gaze location" on takeover-quality measures.

Takeover-quality variables		Gaze location $\chi^2(3)$	Gaze location *p*
Long. Control	MLONGA	14.897*	0.002
	MAXLONGD	4.317	0.229
	MAXV	8.973*	0.030
	MINV	3.420	0.331
	DTC	0.865	0.834
	TTC	0.846	0.838
Lat. Control	MLATA	1.762	0.623
	MAXLATAA	1.042	0.791
	SDLP	0.651	0.885

Note. *: $p < 0.05$

In this study, we can differentiate the effects of NDRT attributes on takeover performance using driving behavior measures. We found that drivers had difficulty in performing lateral or longitudinal control of the car after reengaging control during tasks requiring a large cognitive load. In line with the findings of previous research (Engström et al., 2005; Zeeb et al., 2015), it is likely that drivers could not perform the driving tasks because of being out of the loop and having low situation awareness, even though their hands and eyes returned to the steering wheel and road.

On the other hand, we found that the effects of physical and visual NDRT attributes were weaker than cognitive load attributes, because it is easier for drivers to move their hands, feet, and eyes where they are needed as a reflexive response. Regardless of whether or not drivers took a short time to physically return to driving, they were not properly prepared for driving. However, Wandtner et al. (2018) reported that there was a significant effect of "hand in use" on mean longitudinal acceleration, possibly because the categorization of NDRT characteristics was different from that in our study. Wandtner et al. (2018) focused on a combination of modalities used for NDRTs and how they affect the minimum time to collision, considering the interaction effect between each modality. In this study, we differentiated and focused only on the effect of each attribute. Thus, the only measure with a significant main effect on the mean longitudinal acceleration

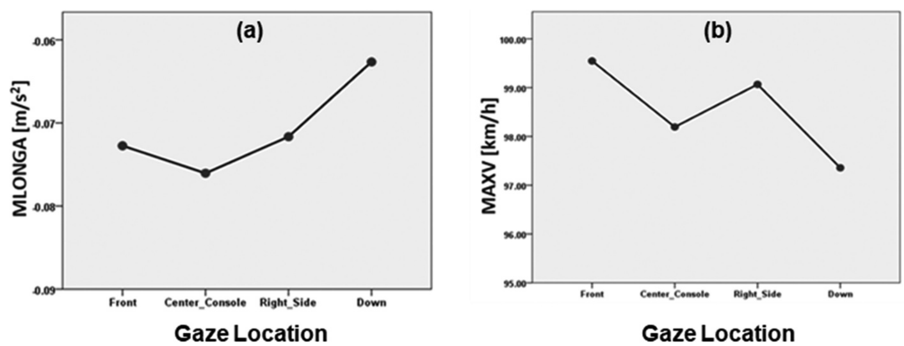

Figure 4. Visual attribute effects on (a) mean longitudinal acceleration and (b) maximum velocity.

for physical NDRT attributes was "hand in use." Interestingly, there was no significant difference between the one- and both-hand conditions, while the largest mean longitudinal deceleration occurred with no hands in use. That is, as indicated in the literature, physical attributes do not have a significant effect on the manual driving performance; rather, it affects the timing aspects of the takeover process, such as the time needed to reach and take control of the steering wheel.

The "gaze location" on the NDRT showed a significant difference in maximum velocity during manual driving. Most of the participants that had their eyes on the road while performing the NDRT had a mean maximum velocity of approximately 100 km/h, while the least mean velocity occurred with their gaze down. The differences in how attentive subjects were under the driving condition during automated driving affected the speed control after regaining vehicle control. Thus, having their gaze down provided blank intervals of information compared to other conditions during automated driving. This indicates that drivers whose visual attention was focused on the road all the time were less sensitive to speed control, thus being able to reach a higher speed. The results can also be observed for the mean longitudinal acceleration, where drivers in the downward condition attempted to maintain a certain speed for a certain period, while those with visual attention on the loop changed their speed during manual driving. That is, a gaze condition under which the participants were not allowed to be attentive during automated driving forced the drivers to speed down the vehicle immediately after regaining vehicle control, due to lack of information on the road situation.

From the analysis of previous research, we can deduce that while takeover time is more of a reflexive and automated reaction of the switching process, the takeover quality is a more time-demanding task associated with how quickly drivers can gain situation awareness for manual driving demand. The results of this study provide further understanding of drivers' behavior in the process of transition of control in HAD when engaged in an NDRT. To reinforce the present study, future research should consider the following points. First, in a driving simulator, the perceived urgency and severity of the given situation is lesser than that in a real driving scenario, which means that the driver can be more engaged in NDRT during the experimental session. Therefore, future research should investigate the effect of NDRTs in a real driving context. Second, we decide to use natural NDRTs to consider ecological validity. The choice between two opposite validities (internal control and ecological) is always correlated to each other; thus, future research should also consider internal validity aspects. Finally, the participants in this study were relatively young drivers. Future studies should consider middle-aged or older drivers to widen the understanding of NDRTs on takeover performance.

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Data availability

Data available with reasonable request (due to privacy/ethical restrictions)

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