Assessing the Effect of Long-Automated Driving Operation, Repeated Take-Over Requests, and Driver's Characteristics on Commercial Motor Vehicle Drivers' Driving Behavior and Reaction Time in Highly Automated Vehicles

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Abstract

Automated Commercial Motor Vehicles (CMVs) have the potential to reduce the occurrence of crashes, enhance traffic flow, and reduce the stress of driving to a larger extent. Since fully automated driving (SAE Level 5) is not yet available, automated driving systems cannot perform all driving tasks under all road conditions. Drivers need to regain the vehicle's control when the system reaches its maximum operational capabilities. This transition from automated to manual is referred as Take-Over Request (TOR). Evaluating driver's performance after TORs and assessing effective parameters have gained much attention in recent years. However, assessing CMV drivers' driving behavior after TOR and the effect of long-automated driving and repeated TORs are not addressed. This paper aims to address this gap and gain behavioral insights into CMV drivers' driving behavior after TOR and assess the effect of the duration of automated operation before TOR, repeated TORs, and driver characteristics (e.g., age, gender, education, and driving history). To accomplish this, we designed a 40-minutes experiment on a driving simulator and assessed the responses of certified CMV drivers to TORs. Drivers' reaction time and driving behavior indices (e.g., acceleration, velocity, and headway) are compared to continuous manual driving to measure driving behavior differences. Results showed that CMV drivers' driving behavior changes significantly after the transition to manual regardless of the number of TORs and the duration of automated driving. Findings suggest that 30 minutes of automated operation intensifies the effect of TOR on driving behaviors. In addition, repeated TOR improves reaction times to TOR and reduces drivers' maximum and minimum speed after TORs. Driver's age and driving history showed significant effects on reaction time and some driving behavior indices. The findings of this paper provide valuable information to automotive companies and transportation planners on the nature of driver behavior changes due to the carryover effects of manual driving right after automated driving episodes in highly automated vehicles.

Keywords: Take-Over Request; Commercial Motor Vehicle; Long-automated Operation; Repeated Take-Over Requests; Driver Factors; Driving Simulator.

1. Introduction

The idea of a fully automated vehicle is not new anymore, however, the implementation of this technology has gained more attention, in recent years. Until automated driving systems can perform all driving tasks under all road conditions (full automation, level 5, based on SAE International definitions (SAE., 2018)), drivers will have to take over the vehicle control when the automation reaches its operational limits in level 4 (highly automated), due to the road conditions, critical events, and system failure. In this non-ideal automated driving condition, although the system can perform all driving tasks and even intervene in some cases of a critical event or system failure, driver interaction is needed if the system initiates a Take-Over-Request (TOR) to the driver. Driver's performance after the transition from automated to manual driving is an important issue in the automated vehicle's safety studies, specifically, in automation level 4 (highly automated), since monitoring the system performance and environment condition is not needed and drivers can engage in non-driving tasks during the automated operation. Previous studies showed that drivers' behavior after the transition to manual would be different compared to continuous manual driving (Stanton & Young, 1998; Merat & Jamson, 2009; Brandenburg & Skottke, 2014; Varotto et al., 2015; Vlakveld et al., 2018; Vogelpohl et al., 2018). While De Winter, Happee, Martens, and Stanton (2014) showed that these changes are more significant in highly automated vehicles (level 4) compared to conditionally automated vehicles (level 3).

In literature, most studies reviewed passenger car driving behavior after TORs, while a significant proportion of vehicles in the US are Commercial Motor vehicles (CMV) and CMV drivers have specific attributes that necessitate more research on their performance in TOR conditions. CMV drivers usually have to drive under time pressure, which increases the risk of crashes. They should drive to predefined destinations and are restricted to predefined roads. Moreover, their jobs are underling to their driving behavior and driving records, therefore, they can lose their job in case of unsafe driving behavior and associated accidents. In addition, U.S. surface freight transportation would increase by up to 37% by 2045 (Hwang et al., 2016). This ever-increasing rate of freight transportation has attracted more attention to CMVs' safety. Deployment of automated CMV (Level 4) has the potential to dramatically improve the safety performance of CMVs.

It is forecasted that CMVs will be the first to be adopted automated vehicle technology (i.e., Level 4) compared to passenger vehicles as organizational adoptions historically occur first compared to individual adoption. Several companies have invested in automated CMV technologies such as Otto/Uber, Waymo/Google, Tesla, Volvo, Embark, Daimler/ Mercedes. Until the full automation (level 5 automation) is not completely implemented, CMVs' drivers' behavior during and after TORs in level 4 automation should be considered. Limited studies have been conducted in this area. Zhang, De Winter, Varotto, Happee, and Martens (2019) evaluated truck drivers' reaction time during the TOR considering three different levels of automated operation monitoring and under platooning scenarios and used the eye movement measure for evaluating drivers' behavior. Heikoop, De Winter, Van Arem, and Stanton (2018) reviewed the effects of mental demand tasks on situation awareness in connected platoon scenarios. Situation awareness, self-reported workload, and physiological state were measured in three levels of task demand (low, medium, and high). Hence, this paper aims to assess driving behavior changes after the transition from automated to manual driving in a highly automated vehicle (level 4) condition, targeting Commercial Motor Vehicle (CMV) drivers.

1.1. Background studies

Analyzing drivers' driving behavior during and after a TOR is a widely studied area. Researchers assessed the driving behavior and their reaction to TORs to evaluate different effective parameters in the transition from automated to manual driving. For instance, in an early study, drivers braking inputs and steering wheel angle to assess drivers' required time to get back into the driving loop after TOR in conditional automated driving were evaluated. Results showed that drivers' decision-making and reactions are faster by generally worse in quality (Gold et al., 2013). Brandenburg and Scottie (2014) evaluated driving behavior in highly automated driving and considering a platoon scenario. Results showed that drivers significantly decreased their distance to the lead vehicle in the post-automation driving period compared to their pre-automation duration. Louw, Merat, and Jamson (2015) investigated the effect of engaging in a reading task during vehicle automation on drivers' ability to resume manual control and avoid an impending collision with a stationary vehicle. They compared drivers' reactions to the stationary vehicle in manual control to two automation conditions. Findings suggested that drivers were slower to identify the potential collision scenario in TOR conditions. Madigan, Louw, and Merat (2018) focused on evaluating drivers' lane changing to assess changes in driving behaviors in a highway hazard scenario. Results showed that drives' vehicle control after TOR is degraded compared to manual driving. Drivers had higher deviation in lane positioning and speed, along with higher lateral acceleration during lane changing. Kim et al. (2018) analyzed divers' TOR reaction time when they are switching to manual driving while performing non-driving secondary tasks. The results show that drivers need different reflective reaction times depending on the secondary tasks and thus need to consider different types of TORs based on the status of the driver. In a recent study, Mahajan, Large, Burnett, and Velaga (2021) assessed the driver's behavior in conditional automated driving and evaluate the effect of voice assistance investigated the role of an in-vehicle digital voice assistant. The results showed that the voice assistant increased the likelihood of making a timely takeover by 39%. There was also some evidence suggesting that male drivers are likely to resume control 1.21 times earlier than female drivers.

Since the purpose of this research is to assess the effect of duration of automated operation, repeated TOR, and driver's characteristics on CMV drivers driving behavior after TORs, related studies to these topics are reviewed in more detail in the following sections.

1.1.1. Duration of automated operation

In literature, only a few studies have been conducted to assess the effect of automated driving duration on the drivers' driving performance while the results are varied. Funkhouser and Drews (2016) measured drivers' heart rate during and after take-over considering different automated operation duration. But they did not compare driving performance between scenarios. They stated that "we expect to find a significant increase in reaction time the longer participants are in automated mode, disengaged from the task of driving". Later Feldhütter, Gold, Schneider, and Bengler (2017) evaluated drivers' reaction time, time to collision, acceleration, and lateral acceleration in two different automated driving duration scenarios, a short segment with 5 minutes and a long segment with 20 minutes of automated driving. They found that the reaction time is increased in the longer automated driving scenario, while the driving performance did not change noticeably. Jarosch and Bengler (2018) compared take-over situations of two studies that just differed in the duration of the automated driving, respectively 25 and 50 minutes of conditional automated driving. The take-over performance of the participants was rated using the video-based TOC expert rating tool by three trained raters. Results showed that take-over performance differs among individuals and that such take-over situations can cause problems for most of the participants. Especially in long conditional automated driving, the human driver needs to be supported in TOR conditions. They stated that the influence of the duration of automated operation seems to be stronger than that of the non-driving related task. Bourrelly et al. (2019) found that about 1 hour of automated driving affected the driver's behavior and leads to poorer take-over performance, longer reaction time, and sharper avoidance maneuvers. A recent study investigated how automation duration affects drivers' take-over response quality and driving performance in a road-work zone (Pipkorn et al., 2021). Results showed that compared to manual driving, drivers started their steering maneuvers earlier or at similar times after automated driving, and none of the drivers crashed. However, slight increases in vehicle speed and accelerations were observed after exposure to automation. This study did not observe as large automation aftereffects in long-automated operations on the test track as previously found in driving simulator studies.

1.1.2. Repeated exposure to TOR

Assessing the effect of repeated exposure to TOR is more common in the literature compared to the duration of automated operation. Russell et al. (2016) discussed the effect of motor learning on car-to-drive handover in automated vehicles. They showed that drivers show more closed-loop corrective steering behavior after takeovers than in manual driving but this effect dissipates after 10 repetitions. Kreuzmair, Gold, and Meyer (2017) stated that repeated exposures mediate the effect of factors such as fatigue and learning effects of additional iterations lead to improving take-over performance. Petermeijer, Bazilinskyy, Bengler, and De Winter (2017) showed that repeated experimental exposures have significant effects on action decisions and post takeover control. They designed three sessions in a highly automated car, each session with a different TOR modality (auditory, vibrotactile, and auditory-vibrotactile). Six TORs were provided per session, warning the participants about a stationary vehicle that had to be avoided by changing lanes left or right. Results showed that drivers tend to brake less often following repeated exposures, although the effect may be kinematics dependent. Gold, Happee, and Bengler (2018) presented models predicting the main take-over performance variables, take-over time, minimum TTC, brake application, and crash probability in conditionally automated vehicles. They stated that repetitions of takeover scenarios result in a significantly lower likelihood of a crash and higher TTC. Hergeth, Lorenz, and Krems (2017) investigated the effects of prior familiarization with TORs during conditional automated driving on drivers' initial takeover performance and automation trust. As hypothesized, prior familiarization with TORs had a more positive effect on takeover performance in the first than in a subsequent takeover situation. In all groups, automation trust increased after participants experienced the system. Participants who were given no prior familiarization with TORs reported highest automation trust both before and after experiencing the system. In term of driving behavior, drivers showed lower maximum resultant acceleration (square root of the sum of square maximum lateral and longitudinal accelerations). Roche, Somieski, and Brandenburg (2019) followed two objectives in their study. First, they examined the effects of the TOR design (auditory or visual-auditory) and the NDRT modality (auditory or visual) on driver behavior and their experience of the situation. Second, drivers' behavioral changes to the repeated experience of takeover situations were assessed. The results revealed that repeatedly experiencing three takeover situations with an auditory TOR lengthens the minimum TTC. Moreover, subjective workload decreased over all six takeover situations experienced by the participant. Forster et al. (2019) discussed the effect of learning in perceptual-motor skills, decision-making and problem-solving. They stated that with repeated interaction, users of driving automation will show increased performance due to enhanced understanding of the way how to execute the control transitions. Brandenburg and Roche (2020) addressed assessing the effect of repeated TOR considering different level of visibility. One of the goals of their study was to assess how drivers change their behavior with the repeated experience of a takeover situation with the same visibility (fog or no fog). In this study, participants' takeover time, minimum TTC, deceleration, and maximum steering behavior were the dependent variables. Results showed that, drivers partially adapt their takeover behavior to the repeated experience of takeover requests.

1.1.3. Driver's characteristics

In addition to characteristics of TORs and automated operations, researchers explored the effects of various driver factors on reaction time and takeover performance. In this regard, the interaction of driver's age and driving behavior after TOR has received more attention. Clark, McLaughlin, Williams, and Feng (2017) detected no impact of age on hands-on reaction time or feet-on reaction time by comparing two groups of young (18–35 years) and older (62–81 years) drivers. Körber, Gold, Lechner, and Bengler (2016) found similar results on takeover time among two age groups spanning 19 years to 28 years of age and 60 years to 79 years of age. However, they showed that older drivers (60–79 years) engaged in more braking and experienced longer minimum TTC and fewer collisions compared with younger drivers (19–28 years). Gold, Happee, and Bengler (2018) found that drivers under 46 would have faster takeover times than the mean. However, they did not find a significant impact of age on crash probability but did show that age had a quadratic effect on the probability of brake application, indicating that drivers between the ages of 39 and 59 years were more likely to push the brake than younger drivers (19–39 years) or older drivers (older than 59 years). Li, Blythe, Guo, and Namdeo (2018) by reviewing two groups of young (20–35 years) and old (60–81 years) age drivers, found that the older group have considerably slower reaction time (defined as eyes-on, hands-on, and feet-on time), indicator time, and takeover time compared with the younger group. Moreover, they showed that older drivers demonstrate shorter minimum TTC, greater resultant acceleration, and greater deviation of the steering wheel angle and had more collisions than younger drivers. Clark and Feng (2017) found that older drivers (62–81 years) deviated less from the road centerline and drove at a slower speed compared with younger drivers (18–35 years), although older drivers applied more pressure on the brake pedal.

1.2.Literature gaps

Considering the best efforts for evaluating driving behavior after TOR in literature, assessing CMV driver's driving behavior after TOR, using driving behavior indices, and detecting effective parameters are not addressed. While, as mentioned earlier, it is forecasted that CMVs will be the first generation of vast adoption of highly automated driving technology. Moreover, transportation planners are planning to incorporate truck platooning to increase the safety and efficiency of freight transportation. Implementation of truck platooning necessitates the application of highly automated driving and connected vehicles (Sweatman, 2017). Therefore, assessing CMV drivers' driving behavior and effective parameters in this group is essential. In addition, due to the huge capital investment needed for infrastructure improvement, it is expected that higher functional classes of highway (e.g., Interstate highways and expressways) will be ready for highly automated driving first and gradually other functional classes of highways (e.g., US highways, state highways, city/county roads) will be upgraded for autonomous driving. Thus, drivers of the first generation of highly automated CMVs must take over vehicle control often in consecutive autonomous driving episodes followed by non-autonomous driving episodes (on state, local highways) frequently. Therefore, evaluating the effect of repeated exposure to TOR becomes important for CMV drives, although valuable efforts have been devoted to assessing the effect of repeated TOR in literature for passenger cars. Furthermore, since higher functional classes of highways usually are used for long-distance trips, the effect of long-automated operation becomes important. While the literature did not provide consistent answers for the effects of long-duration automated operations which necessitate more research in this area. Finally, literature reviews showed that the findings on the interaction of driver's characteristics and post-takeover control are similarly inconsistent (McDonald et al., 2019), hence more research on this area is recommended. In addition, although assessing the effect of drivers' age witnessed many studies, other drivers' factors (e.g., driving history, years of experience) are not addressed. Besides, assessing the interaction between driver's characteristics and their driving performance can reveal hidden aspects of TOR in highly automated vehicles is always an important subject (Li et al., 2018).

1.3. Objectives and hypothesis

The first objective of this research is to investigate the CMV drivers' driving behavior during and after the transition from automated to manual driving (during and after TORs) in highly automated vehicles (level 4). In this regard, a simulation experiment is designed on a driving simulator (RDS-500) and 45 CMV drivers are recruited to participate in the designed experiment. Drivers' responses to critical events in continuous manual driving and highly automated driving condition are compared together. Drivers' reaction time to the TOR, acceleration/deceleration rate, speed, Time to Collision (TTC), headway distance, the standard deviation of lateral positioning (SDLP), heading error, lateral acceleration, and lateral speed are recorded constantly during the simulator experiment.

The second research objective is to investigate the effect of automated operation duration on CMV drivers' driving behavior. Participants' driving behavior is evaluated in 3 different automated operation duration- 5 minutes, 15 minutes, and 30 minutes- to assess the effect of different duration of automated operation. This paper aims to investigate if the long-automated operation would intensify the effect of TORs or not.

The third objective of this research is to investigate CMV drivers' behavior after a sequence of TORs (repeated TORs). This paper aims to evaluate if driver's behavior will improve after repeated transitions from automated to manual driving. In other words, are drivers able to transfer their experience in managing a TOR condition and adapt their driving behavior to this condition?

Finally, the fourth and last objective of this research is to assess the interaction between CMV drivers' characteristics and their driving behavior after TOR. The concentration of this paper is on drivers' age, education, and driving history (driving experience, traffic tickets, car crashes, and annual driven mileage).

To accomplish the above-mentioned research objectives, four hypotheses are defined and are tested in this study:

- Hypothesis 1: CMV drivers' driving behavior is affected by the transition from automated operations compared to manual operations (Objective 1).
- Hypothesis 2: CMV drivers' driving behavior depends on the duration of automated operations before transitioning to non-automated operations (Objective 2).
- Hypothesis 3: CMV drivers' driving behavior would improve after a sequence of TORs (Objective 3).
- Hypothesis 4: CMV drivers driving behavior after TOR is related to drivers' age, gender, education, driving experience, and driving history (Objective 4).

To sum up, the contribution of this paper is fourfold. First, analyzing CMV driver driving behavior in a TOR condition. Second, evaluating the effect of repeated TOR in a long-automated operation, Third, assessing the effect of the duration of automated operation and the effectiveness of splitting a long-automated operation into shorter segments. Fourth, evaluating the effect of CMV drivers' characteristics on their performance after TORs.

2. Method

2.1. Participants

45 Commercial drivers (forty male and five females) aged between 22 and 59 years (mean= 34.93, SD=9.60 years) with a minimum of one year of CMV driving experience and a minimum of 15,000 kilometers driving per year, were recruited to take part in this study. Individual participants were recruited using flyers, posters, and social media. Tennessee Trucking Association and IMC companies helped us with recruiting participants and distributing the flyers and posters. Participants were paid $40 for taking the experiment. No additional criteria were used for recruiting participants. Participants driving history (i.e., number of crashes, tickets, and annual mileage), and some demographic information (i.e., gender, age, and education) were collected through a questionnaire. Among 45 participants, 8 participants reported that they had car crashes in their driving history and 10 participants had received at least one ticket in the last two years. Participants' driving experience range was between one to 43 years and mostly had a college degree. Participants were randomly divided into three groups of 15 (Group A, B, and C) and were asked to consider an hour in their schedule for the entire procedure. The experimental and subject recruitment procedures were all approved by the Institutional Review Board (IRB) of the University of Memphis (IRB#: PRO-FY2020-471).

2.2. Apparatus

This research is conducted at the University of Memphis Driving Simulator lab, using RDS-500, a research driving simulator (developed by Real-time Technologies LLC.). RDS-500 uses three robust software, SimCreator 3.8, SimCreator DX, and SimVista, developed for high-fidelity research simulators. SimCreator is a graphical, hierarchical, real-time simulation and modeling system. SimCreator DX allows researchers to develop scenarios with pre-defined configurable behaviors called maneuvers. Also, SimCreator DX allows users to observe the current state of the SimCreator simulation through graphical displays and detailed data views. It is intended to be the primary tool used for the development, tuning, and experimenter of Experiments. SimVista is a tile-based scene and scenario authoring system that offers the tools to create comprehensive simulation scenarios' environment. RDS-500 has an operator station laptop and a high-end simulation computer with one 55-inch HD monitor and a USB-based steering wheel and pedal set along with a 5.1 surround sound audio system.

2.3. Procedure and experiment

Upon arrival, first, the procedure and the purpose of the research were explained to the participants. They received a handout containing the instruction for the experiment and essential information about the driving simulator. Driving simulators' parts and functionality of keys were explained to the participants.

Second, before starting the experiment, participants had a 5-10 minute test drive. As participants did not have the experience of driving on a simulator, test drive allows them to get used to the driving simulator. During the test drive, participants test the sensitivity of the pedals and steering wheel and become familiar with the experiment's environment. The transition from manual to automated operation and the reverse were tested several times to make sure that participants are fully comfortable with the transition process. In this study, participants needed to press a button on the steering wheel to activate the automated driving, and to cancel the automated driving, they needed to depress the brake pedal. The test drive section was designed precisely to eliminate the errors that the first experience of driving with a driving simulator may cause. Moreover, during the test drive section participants practice one TOR condition. This TOR condition does not contain a critical event and is designed only to show participants how a TOR works. In this study, take-overs were requested by an auditory alert, playing 10 seconds before the system reaches its limits. This time is known as the budget time (the time between the system limit and when the system should send the takeover request). Researchers addressed this time and different studies came up with different adequate budget-time to have appropriate and safe take-over performance. Walch et al. (2017) discussed 17 take-over studies, focusing on the effect of the time budget, traffic complexity, non-driving task, and driver age. The authors concluded that 10 seconds are an adequate time budget while pointing out that the driver's state and situational circumstances affect the driver's ability to take over control. Hence, in this study the budget time is equal to 10 seconds. No data was collected during the test drive section.

Third, after the test driver section, the experiment starts. A 40-minute experiment was designed in the driving simulator. The environment of the experiment was a separated two-way freeway with two lanes in each direction incorporating two gentle curves (both located at the beginning of the experiment and before critical events) and a speed limit of 110 (km/hr). The starting point was at the entrance of the freeway and the participants had to take out the vehicle from a parked position. During the experiment, participants' driving behaviors were constantly recorded by the simulator. The ambient traffic was regular (10-15 veh/km/ln), and the weather condition was sunny. The designed experiment was divided into two sections. The first section was devoted to manual driving where participants were responsible for all driving tasks (i.e., longitude and lateral control of the vehicle) and must drive for 10 minutes. Two critical events (i.e., a crash and a sudden end of a lane) were designed in this section with a time interval of 5 minutes, where the former happens after 3 minutes of manual driving and the latter after 8 minutes. Critical events in this section (manual driving) happened without a preceding alert. Participants' responses to these two critical events are called *Manual Driving (MD)* in the rest of the paper.

Then, after 10 minutes of manual driving, participants were asked to set on the automated driving. Here the second section starts. The second section contains Highly Automated Driving (HAD) and about 30 minutes duration. The system was responsible for longitudinal and lateral control of the vehicle where the max speed limit was 110 (km/hr), the minimum headway was 1.5 (s) and the Max acceleration and deceleration were considered 1 (m/s^2) and 2 (m/s^2) respectively. These limits were fixed, and participants could not change them. The automated operation section is divided into three scenarios. Each group of participants was assigned to one scenario, Group A, B, and C followed scenarios A, B, and C, respectively (Scenarios are demonstrated in Fig. 1). The first scenario consists of six take-over conditions with a fixed time interval of 5 minutes. The second scenario contains two take-over conditions with 15 minutes time intervals. Finally, the third scenario contained one take-over condition which occurred after 30 minutes of automated operation. Fig. 1 demonstrates the designed experiment's sections and scenarios. After each take-over, participants had to drive for 1 minute and then reactivate the automated driving. Participants' driving behavior during the first 20 seconds of this period (20 seconds from the moment of regaining vehicle control) is compared to their driving behavior in the corresponding period of time during the MD[1] to assess the driving behavior changes caused by TOR.

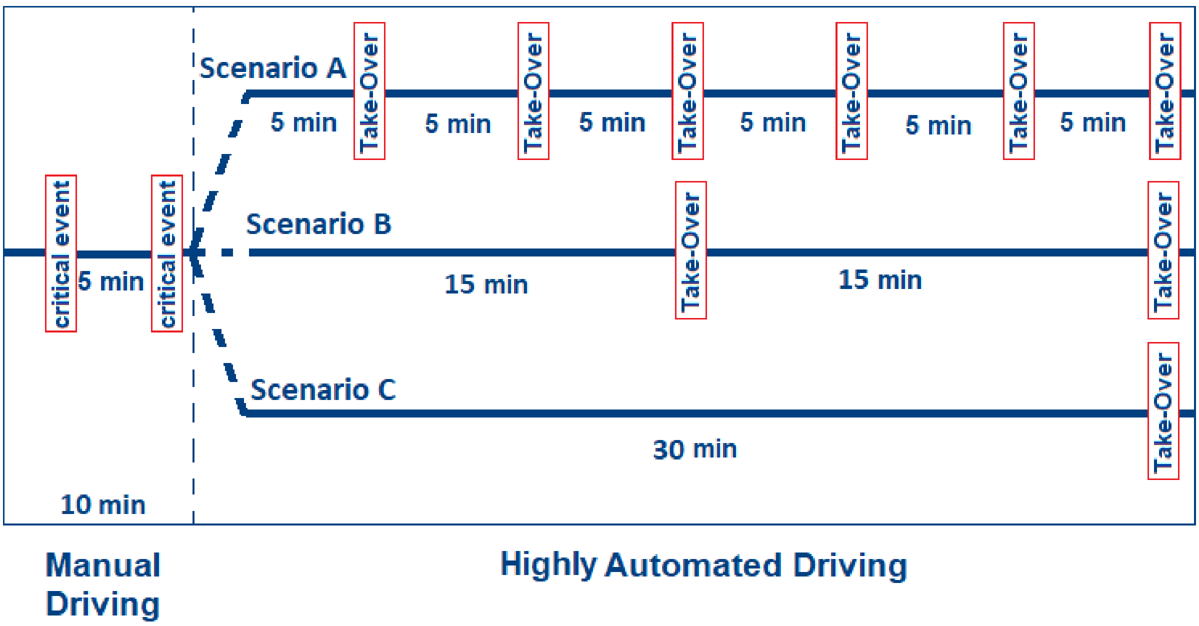
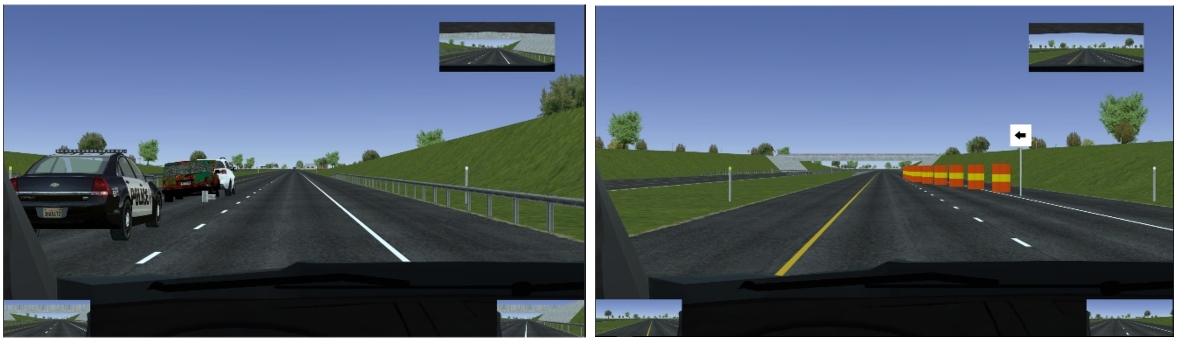


Fig. 1. The schematic of the designed experiment

In this study, critical events, which lead the system to reaches its limits, are generally achieved by a road capacity reduction. Two critical events were defined in this study, (i) a car crash scene with two cars, and (ii) a sudden end of a lane due to road construction, stationary vehicle, and obstacles. All the events occurred in the lane the vehicle is driven on, to force the participants to take action or take over vehicle control (in both sections, manual and automated driving). To avoid participants' prediction of the condition, the feature of the events was

[1] Since the critical events (both during the MD and HAD) are triggered on time-based order (instead of distance base), the analyzing interval section in MD is considered from 10 seconds before the critical event (the budget time in TOR) to 10 seconds after critical events.

different; While the geometry of the event (e.g., length, width, and effective critical area) was the same. Two examples of the designed critical events are provided in Fig. 2.



a. A two-car crash with police car **b. Construction zone**

Fig. 2. Two examples of a critical event in the designed experiment

2.4. Dependent and independent variables

The present study addresses the CMV driving behavior changes subject to the take-over condition, considering different automated operation duration and repeated TOR. To accomplish this goal, participants' responses to critical events during and after the automated operation is compared to their manual driving behavior. The following variables are collected for assessing participants' Driving behavior.

Reaction times are collected after each TOR. Reaction time refers to the period of time between playing the TOR alert by the system and depressing the brake pedal to regain vehicle control. In addition to reaction time, mean speed**,** maximum speed, maximum lateral speed, maximum acceleration, mean acceleration, maximum deceleration, maximum lateral acceleration, the Standard Deviation of Lateral Positioning (SDLP), minimum Time to Collision (TTC), minimum headway distance (the minimum distance between the vehicle and the front vehicle), and max heading error (the maximum angel between the road center and vehicle's heading. This index indicates the smoothness of lane changing). All dependent variables are tabulated in Table 1.

Table 1. List of dependent variables

Dependent Variables	Unit	Direction	Description
Reaction time	s	N/A	
Speed	m/s	Longitudinal and lateral	Max, Min, and Mean
Acceleration	m/s^2	Longitudinal and lateral	Max and Mean
Deceleration	m/s^2	Longitudinal	Max
SDLP	m	Lateral	Standard Deviation
Time to Collision	s	Longitudinal	Min
Headway distance	m	Longitudinal	Min
Heading error	rad	N/A	Max

In this study, independent variables are defined as driving modes (MD/HAD), the duration of automated operation, the number of TOR in an automated operation, drivers' gender, age, years of experience, education, the number of crashes, the number of tickets in the past two years, and the annual driven mileage. All independent variables are categorical and tabulated with more detail in Table 2.

Table 2. List of independent variables

Independent variable	Categories	Description
Driving mode	2	0= manual driving and 1= highly automated driving
Duration of automated driving	4	0= manual driving, 1= 5 minutes, 2= 15 minutes, and 3= 30 minutes
The number of TORs	7	0= manual driving, 1= 1 TOR, 2= 2 TORs, … 6= 6 TORs
Gender	2	0= female and 1= male
Age	4	1=less than 30 years old, 2= between 30 to 40, 3= between 30 to 50, and 4= more than 50
Education	4	1= high school diploma or less, 2= college degree, 3= associate degree, 4= bachelor's or higher degree
Years of driving experience	5	1= less than 5 years, 2= between 5 to 10, 3= between 10 to 15, 4= between 15 to 20, and 5= more than 20
Having car crashes	2	0= no crashes and 1= having car crashes in driving history
Receiving tickets	2	0= no tickets and 1= receiving tickets in the past two years in driving history
Annual mileage	4	1= 15,000 to 20,000 km, 2=20,000 to 25,000 km, 3= 25,000 to 30,000 km, and 4= > 30,000 km

2.5. Statistical analysis

In this paper, Multilevel Mixed Linear Model (MMLM) is applied to test the hypothesis of this study. The application of MMLM recently started to become widely disseminated in psychology (Klüver et al., 2016). Since in this study driving behavior of each participant was measured multiple times (i.e., manual driving and automated driving) observations are not completely independent, as is assumed by standard regression methods. Ignoring the clustering of data might lead to deflated standard errors and fallacious significant effects. MMLM, however, take into account the hierarchical (nested) structure of the data. MMLM estimates the fixed-effects parameters for the observed data and the variance of the random effects (Goldstein, 1986). In this paper, a two-level MMLM is fitted for each of the dependent variables (presented in Table 1) with participants on the second level and observation on the first level. In the fixed part, we entered the independent variables as the main effects as well as the interaction between the duration of automated operation and the number of TOR ($Duration \times Num.of\ TOR$) and the interaction between driving mode and drivers' characteristics (i.e., $Driving\ Mode \times Gender$). In the random part, we entered a random intercept as well as a random slope for the driving mode. Thus, the random part corresponds to the "maximal" random effects structure justified by the design as recommended by (Barr et al., 2013)for hypothesis testing. Barr, Levy, Scheepers, and Tily (2013) suggested that if a factor is between-subject, then a random intercept is usually sufficient. If a factor is within-subject and there are multiple observations per treatment level per unit, then a by-subject slope is needed for the factor.

Based on Goldstein (1986), considering the measurements on a response variable (Y_{si}) for the i^{th} measurement for the s^{th} subject (participant) we can write the model as:

$$Y_{si} = \beta_0 + S_{0s} + (\beta_1 + S_{1s})X_i + e_{si}\ , \tag{1}$$
$$(S_{0s}, S_{1s}) \sim N\left(0, \begin{bmatrix} \tau_{00}^2 & \rho\tau_{00}\tau_{11} \\ \rho\tau_{00}\tau_{11} & \tau_{01}^2 \end{bmatrix}\right),$$
$$e_{si} \sim N(0, \sigma^2)$$

Where, β_0 and β_1 are respectively the intercept and the slope of the fixed effect parameters, S_{0s} are the random intercepts with variance τ_{00}^2 and they allow intercept terms to vary across subjects (participants). S_{1s} is the random slope term with variance τ_{01}^2. Considering $S_{0s}$and S_{1s}, we assume that random intercept and slope are distributed bivariate normal with a mean (0,0) and three parameters, τ_{00}^2 (random intercept variance), τ_{01}^2(random slope variance), and $\rho\tau_{00}\tau_{11}$ (random intercept/slope covariance). $e_{si}{\sim}N(0,\sigma^2)$ indicates that the error term is normally distributed with mean 0 and variance σ^2.

To complement the developed models, elasticity analyses were conducted to determine the magnitude of the effects of independent variables on dependent variables. The elasticity analyses indicate the response of the dependent variable for a 1% change in an independent variable. The standard elasticity calculations apply to continuous variables. Since in this paper, independent variables are categorical, pseudo-elasticity effects were calculated for such variables. Based on (Washington et al., 2020), the elasticity of a dependent variable Y with respect to a continuous independent variable X that has a regression coefficient β can be defined as:

$$e_i = \beta_i \frac{X_i}{Y_i} \approx \frac{\partial X_i}{\partial Y_i} \times \frac{X_i}{Y_i} \tag{2}$$

Therefore, the pseudo-elasticity for categorical variables is defined as follow:

$$E_{X_i}^{Y_i} = \frac{EXP(\beta_i) - 1}{EXP(\beta_i)} \tag{3}$$

3. Results

This section presents participants' reaction time and driving behavior measures during the experiment, as well as the results of applying statistical analysis on the data collected for 45 participants. During the data collection, we had to restart the experiment for one of our participants, due to the simulator crash. The simulator crash was at the beginning of the experiment (middle of manual driving section) and the participants kindly accepted to restart the test.

To provide a general view of the participants' performances the mean and standard deviation of all dependent variables are provided for each group in Table 3. Moreover, the results of fitting MMLM on reaction time and drivers' behavior are provided in this section. In this study, MMLM models were fitted using RStudio (version 3.6.2) and lme4 package (Bates et al., 2014). All independent variables are coded as categorical variables. After model fitting, the residuals of the models predicting were not normally distributed, as it is assumed in regression models, therefore, logarithm transformation is taken for all dependent variables, and the models have fitted again. Also, we removed the years of driving experience from the independent variables due to high multicollinearity. Results of developing models are presented in two forms. First, we present the results in the form of an ANOVA table, since it is more widespread in psychology and interpreting regression coefficients with dummy variables and interactions is somewhat tricky (Klüver et al., 2016). To compute the Type III ANOVAs the afex package is used and the Kenward-Rogers approximation is used for the denominator degrees of freedom. The results of fitted models in ANOVA form are provided in Table 4. In Table 4, for brevity purposes, the results are shown only for driving mode, referring to Manual Driving (MD) or Highly Automated Driving (HAD), duration of automated operation, the number of TORs, and the interaction between driving mode and driver's characteristics. Since these are the important factors for testing the hypothesis of this study.

Table 3. The means and standard deviations of all dependent variables for all Manual Driving (MDs) and Take-Over Requests (TORs)

	Group A							Group B			Group C	
Variable	**MD**	**TOR1**	**TOR2**	**TOR3**	**TOR4**	**TOR5**	**TOR6**	**MD**	**TOR1**	**TOR2**	**MD**	**TOR 1**
Reaction Time	-	3.046 (1.917)	2.348 (1.196)	2.416 (1.097)	2.69 (1.683)	2.311 (1.132)	1.966 (0.809)	-	3.219 (1.562)	2.328 (0.889)	-	3.238 (1.017)
Max. Acceleration	1.104 (1.579)	0.902 (0.875)	1.202 (1.181)	1.289 (1.535)	1.077 (0.828)	1.204 (1.749)	1.119 (1.063)	0.803 (1.142)	1.24 (0.966)	1.231 (0.943)	0.687 (0.787)	1.404 (1.369)
Max. Deceleration	3.4 (2.544)	5.055 (2.222)	5.665 (4.943)	5.808 (3.759)	5.261 (3.242)	5.858 (2.741)	5.294 (2.805)	2.58 (2.767)	6.459 (5.212)	7.016 (3.721)	2.742 (-2.742)	7.185 (4.91)
Mean Acceleration	-0.547 (0.359)	-0.265 (0.37)	-0.157 (0.386)	-0.343 (0.236)	-0.204 (0.301)	-0.216 (0.319)	-0.043 (0.244)	-0.347 (0.386)	-0.308 (0.448)	-0.043 (0.149)	-0.494 (-0.41)	-0.229 (0.596)
Max. Lateral Acceleration	1.121 (1.323)	1.502 (1.268)	1.162 (1.701)	2.012 (2.457)	1.458 (1.157)	1.711 (2.165)	0.992 (0.299)	1.178 (2.147)	1.885 (2.52)	1.507 (1.252)	1.197 (1.197)	1.588 (1.373)
Max. Heading Error	0.059 (0.002)	0.053 (0.001)	0.139 (0.147)	0.275 (0.278)	0.163 (0.153)	0.267 (0.328)	0.057 (0.01)	0.056 (0.003)	0.178 (0.154)	0.088 (0.044)	0.063 (0.063)	0.053 (0.086)
Min. Headway Distance	64.059 (38.671)	71.608 (63.381)	69.927 (56.966)	65.432 (69.708)	74.75 (69.032)	59.129 (62.085)	55.483 (54.513)	76.263 (30.315)	37.523 (32.81)	51.378 (40.691)	51.463 (35.463)	31.666 (60.41)
Min. TTC	6.581 (4.086)	4.514 (2.438)	8.488 (5.756)	9.814 (5.211)	10.685 (6.432)	6.886 (3.302)	4.71 (2.231)	5.056 (3.542)	6.246 (3.178)	3.865 (3.865)	4.662 (3.265)	7.882 (4.534)
SDLP	0.466 (0.203)	0.43 (0.182)	0.413 (0.183)	0.407 (0.168)	0.357 (0.16)	0.472 (0.173)	0.423 (0.146)	0.548 (0.22)	0.43 (0.156)	0.602 (0.104)	0.556 (0.235)	0.465 (0.197)
Max. Speed	34.61 (4.048)	31.459 (4.032)	31.154 (3.415)	31.636 (2.861)	33.98 (5.826)	30.362 (2.883)	30.592 (3.335)	33.796 (3.263)	29.852 (3.359)	31.559 (3.266)	35.698 (4.023)	31.663 (3.341)
Min. Speed	20.968 (13.877)	16.19 (11.143)	18.55 (9.666)	16.248 (9.428)	25.182 (10.465)	13.279 (9.914)	3.197 (4.749)	23.482 (14.07)	14.452 (10.244)	20.37 (7.674)	23.297 (13.984)	15.299 (11.948)
Mean Speed	28.275 (7.138)	24.955 (5.048)	25.757 (4.701)	24.164 (4.491)	30.069 (8.712)	23.051 (5.028)	24.62 (9.839)	29.482 (6.804)	23.421 (4.118)	26.614 (4.063)	29.693 (6.992)	24.961 (5.219)
Max Lateral Speed	0.166 (0.115)	0.154 (0.146)	0.274 (0.472)	0.332 (0.496)	0.091 (0.057)	0.407 (0.514)	0.213 (0.212)	0.112 (0.121)	0.132 (0.108)	0.139 (0.084)	0.184 (0.2)	0.119 (0.098)

- The values in the parentheses are standard deviations- The values in the parentheses are standard deviations

In the second format, we present the regression output for the entire variables in Appendix A. In appendix A, the coefficients and the t-value of all independent variables and the interaction between them are provided. Moreover, the results of elasticity analyses for all dependent variables are provided in Appendix B, which shows the magnitude of the effect of independent variables on dependent variables. In the following section, results are discussed in detail for each dependent variable separately, except for SDLP, TTC, and mean speed. As Table 4 shows, driving mode (MD/HAD), duration of automated operation, and repeated TOR did not show a significant effect on SDLP, TTC, and mean speed. Hence, the results of these three dependent variables are not discussed in detail. However, modeling results are presented in Table 4 and Appendix A.

Table 4. ANOVA table from the MMLM analysis for all dependent variables.

Dependent variable	Effect	df_1	df_2	F	P
Log (Reaction Time)	Driving Mode	-	-	-	-
	Automated Duration	2	55.3	4.20	0.020*
	Repeated TOR	5	90.7	5.30	<0.001***
	Automated Duration × Number of TOR	8	128.9	72.57	<0.001***
	Driving Mode × Gender	1	48.3	5.49	0.023*
	Driving Mode × Age	3	44.0	4.53	0.008**
	Driving Mode × Education	3	50.6	1.42	0.248
	Driving Mode × Crash	1	44.6	0.18	0.677
	Driving Mode × Tickets	1	46.6	2.57	0.115
	Driving Mode × Mileage	3	44.5	0.57	0.636
Log (Max. Acceleration)	Driving Mode	1	59.0	0.78	0.379
	Automated Duration	3	197.2	2.73	0.045*
	Repeated TOR	5	175.5	0.76	0.582
	Automated Duration × Number of TOR	8	175.5	0.55	0.461
	Driving Mode × Gender	1	100.3	0.79	0.372
	Driving Mode × Age	3	97.3	0.54	0.651
	Driving Mode × Education	3	95.9	0.91	0.442
	Driving Mode × Crash	1	99.2	0.23	0.632
	Driving Mode × Tickets	1	99.1	0.01	0.941
	Driving Mode × Mileage	3	98.1	0.67	0.572
Log (Max. Deceleration)	Driving Mode	1	94.5	9.40	0.003**
	Automated Duration	3	192.9	6.86	<0.001***
	Repeated TOR	5	167.5	0.35	0.883
	Automated Duration × Number of TOR	8	167.4	1.18	0.279
	Driving Mode × Gender	1	95.8	0.01	0.924
	Driving Mode × Age	3	91.2	2.81	0.047*
	Driving Mode × Education	3	102.1	1.36	0.260
	Driving Mode × Crash	1	90.2	0.83	0.364
	Driving Mode × Tickets	1	94.8	1.05	0.308
	Driving Mode × Mileage	3	90.9	4.26	0.007**
Log (Mean Acceleration)	Driving Mode	1	197.8	0.97	0.325
	Automated Duration	3	199.2	2.70	0.047*
	Repeated TOR	5	173.4	1.72	0.132
	Automated Duration × Number of TOR	8	130.8	1.41	0.200
	Driving Mode × Gender	1	196.3	0.17	0.677
	Driving Mode × Age	3	196.3	0.39	0.759
	Driving Mode × Education	3	193.8	0.03	0.993
	Driving Mode × Crash	1	187.1	1.72	0.192
	Driving Mode × Tickets	1	196.4	0.05	0.830
	Driving Mode × Mileage	3	193.8	1.15	0.329

$* \; p < .05$, $** \; p < 0.01$, and $*** \; p < .001$

Table 4 (continued). ANOVA table from the MMLM analysis for all dependent variables.

Dependent variable	Effect	df_1	df_2	F	P
Log (Max. Lateral Acc.)	Driving Mode	1	201.0	5.22	0.029*
	Automated Duration	3	188.9	0.36	0.781
	Repeated TOR	5	169.4	0.59	0.707
	Automated Duration × Number of TOR	8	174.8	0.88	0.535
	Driving Mode × Gender	1	166.1	0.44	0.507
	Driving Mode × Age	3	159.3	0.97	0.409
	Driving Mode × Education	3	169.2	1.80	0.216
	Driving Mode × Crash	1	154.4	4.01	0.046*
	Driving Mode × Tickets	1	160.6	2.30	0.132
	Driving Mode × Mileage	3	155.0	2.60	0.054
Log (Max. Heading Error)	Driving Mode	1	94.5	6.39	0.012*
	Automated Duration	3	202.9	1.55	0.206
	Repeated TOR	5	167.5	1.76	0.124
	Automated Duration × Number of TOR	8	167.4	1.42	0.191
	Driving Mode × Gender	1	95.8	1.62	0.204
	Driving Mode × Age	3	91.2	3.06	0.032*
	Driving Mode × Education	3	102.1	0.89	0.447
	Driving Mode × Crash	1	90.2	0.40	0.528
	Driving Mode × Tickets	1	94.8	1.43	0.233
	Driving Mode × Mileage	3	90.9	2.61	0.053
Log (Min. Headway Distance)	Driving Mode	1	200.4	0.42	0.518
	Automated Duration	3	201.2	2.66	0.047*
	Repeated TOR	5	172.7	1.16	0.328
	Automated Duration × Number of TOR	8	174.7	2.37	0.018*
	Driving Mode × Gender	1	163.3	0.46	0.500
	Driving Mode × Age	3	156.0	1.36	0.255
	Driving Mode × Education	3	166.7	1.89	0.132
	Driving Mode × Crash	1	151.2	1.22	0.270
	Driving Mode × Tickets	1	157.6	6.18	0.014*
	Driving Mode × Mileage	3	151.7	0.95	0.417
Log (Min. TTC)	Driving Mode	1	191.8	0.05	0.824
	Automated Duration	3	169.8	2.10	0.102
	Repeated TOR	5	142.1	1.05	0.391
	Automated Duration × Number of TOR	8	171.5	1.88	0.065
	Driving Mode × Gender	1	139.8	0.31	0.576
	Driving Mode × Age	3	134.1	1.62	0.186
	Driving Mode × Education	3	144.0	1.48	0.220
	Driving Mode × Crash	1	124.8	0.45	0.503
	Driving Mode × Tickets	1	133.6	5.13	0.024*
	Driving Mode × Mileage	3	126.9	0.65	0.585
Log (SDLP)	Driving Mode	1	148.2	1.19	0.277
	Automated Duration	3	204.4	1.82	0.145
	Repeated TOR	5	174.1	0.79	0.560
	Automated Duration × Number of TOR	8	176.4	1.95	0.055
	Driving Mode × Gender	1	99.5	0.09	0.770
	Driving Mode × Age	3	90.5	1.13	0.342
	Driving Mode × Education	3	105.0	0.23	0.877
	Driving Mode × Crash	1	91.7	1.29	0.259
	Driving Mode × Tickets	1	93.2	1.18	0.280
	Driving Mode × Mileage	3	89.0	0.44	0.725

$* \ p < .05$, ** $p < 0.01$, and *** $p < .001$

Table 4 (continued). ANOVA table from the MMLM analysis for all dependent variables.

Dependent variable	Effect	df_1	df_2	F	P
Log (Max. Speed)	Driving Mode	1	200.4	5.98	0.018*
	Automated Duration	3	201.2	1.86	0.144
	Repeated TOR	5	172.7	2.90	0.016*
	Automated Duration × Number of TOR	8	174.7	2.05	0.046*
	Driving Mode × Gender	1	163.3	0.16	0.690
	Driving Mode × Age	3	156.0	1.17	0.342
	Driving Mode × Education	3	166.7	1.03	0.392
	Driving Mode × Crash	1	151.2	2.67	0.114
	Driving Mode × Tickets	1	157.6	7.56	0.011*
	Driving Mode × Mileage	3	151.7	0.13	0.942
Log (Min. Speed)	Driving Mode	1	206.23	14.35	<0.001***
	Automated Duration	3	201.60	9.22	<0.001***
	Repeated TOR	5	175.25	6.08	<0.001***
	Automated Duration × Number of TOR	8	179.78	4.29	<0.001***
	Driving Mode × Gender	1	163.61	0.02	0.899
	Driving Mode × Age	3	150.67	0.75	0.523
	Driving Mode × Education	3	170.46	0.23	0.877
	Driving Mode × Crash	1	156.22	0.58	0.447
	Driving Mode × Tickets	1	155.51	0.50	0.479
	Driving Mode × Mileage	3	150.39	1.48	0.221
Log (Mean Speed)	Driving Mode	1	200.4	0.87	0.352
	Automated Duration	3	201.2	0.46	0.713
	Repeated TOR	5	172.7	1.55	0.178
	Automated Duration × Number of TOR	8	174.7	1.22	0.291
	Driving Mode × Gender	1	163.3	0.06	0.813
	Driving Mode × Age	3	156.0	0.36	0.782
	Driving Mode × Education	3	166.7	0.68	0.563
	Driving Mode × Crash	1	151.2	0.02	0.876
	Driving Mode × Tickets	1	157.6	1.55	0.214
	Driving Mode × Mileage	3	151.7	0.63	0.597
Log (Max. Lateral Speed)	Driving Mode	1	191.8	5.57	0.019*
	Automated Duration	3	69.8	0.28	0.840
	Repeated TOR	5	142.1	0.36	0.873
	Automated Duration × Number of TOR	8	159.5	0.48	0.867
	Driving Mode × Gender	1	139.8	0.92	0.340
	Driving Mode × Age	3	134.1	2.88	0.038*
	Driving Mode × Education	3	144.0	4.08	0.008**
	Driving Mode × Crash	1	124.8	1.43	0.234
	Driving Mode × Tickets	1	133.6	5.02	0.027*
	Driving Mode × Mileage	3	126.9	1.45	0.233

$* \ p < .05$, $** \ p < 0.01$, and $*** \ p < .001$

3.1. Reaction Time

Reaction time refers to the time between the TOR and depressing the brake pedal by the driver. Therefore, in contrast to other dependent variables, reaction time is only calculated for HAD section. Hence, in Table 4, values for the driving mode are blank. Results showed that all participants could regain the vehicle control in 6s and more than 75% of participants regained the vehicle control after 4s. Fig. 3 illustrates the distribution of reaction time among participants. Modeling results showed that the duration of HAD and repeated TOR both have effects on the driver's reaction time to TORs. The reaction time was significantly higher in TOR with 15 minutes ($t = 2.02, p = 0.044$) and 30 minutes of HAD ($t = 2.68, p = 0.007$) compared to 5 minutes of HAD. Elasticity analysis showed that 15 minutes of automated operation will increase the rection time by 21.2% compared to 5 minutes of HAD and 30 minutes of HAD will increase the reaction time by 35.2%. However, drivers' reaction times are improved in a repeated TOR scenario. For instance, after 6 TORs, drivers' reaction time decrease by 48.0%. Among driver factor variables, drivers' gender ($t = 2.34, p = 0.019$) showed significant effects on reaction time, where males had 37.7% longer reaction time compare to females. Moreover, results showed that reaction time increases by 43.8% in drivers with more than 50 years old ($t = 2.05, p = 0.041$). The means and the standard deviation of reaction times in each group and each TOR are presented in Fig. 4.

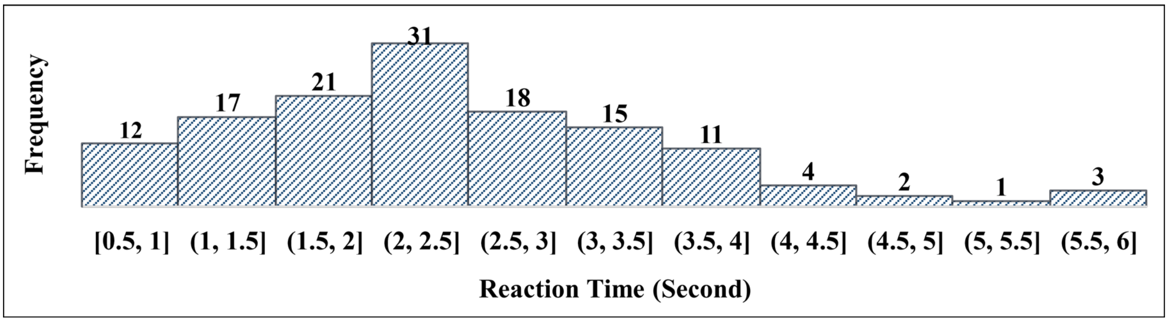


Fig. 3. Distribution of reaction time to TORs

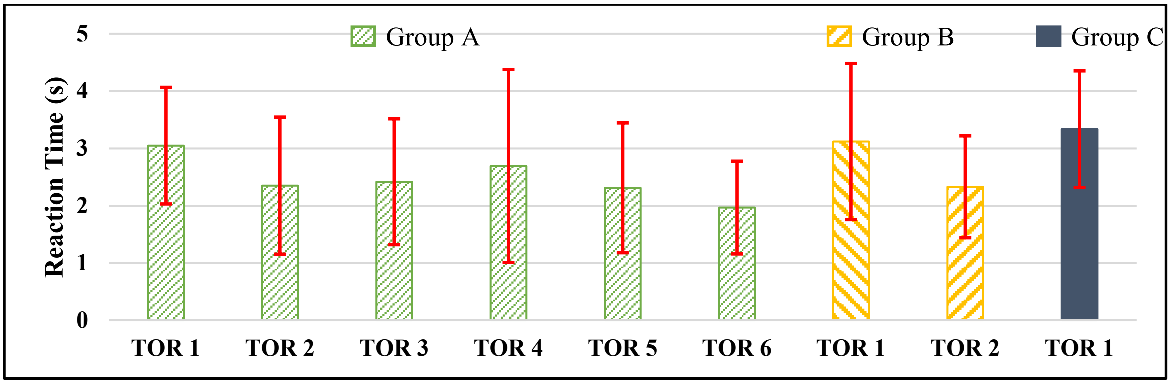


Fig. 4. Comparing the means and standard deviations of reaction time between all groups.

3.2. Maximum Acceleration

Results showed that the duration of HAD before TOR is the only effective parameter in the maximum acceleration of participants after TOR. The only significant coefficient in modeling max acceleration was for 30 minutes of HAD ($t = 2.61, p = 0.0108$) and 30 minutes of HAD would increase maximum acceleration by 84.1%. Thus, considering maximum acceleration, the transition from automated to manual driving only affects maximum acceleration in long-automated driving conditions and increases it. The mean of maximum accelerations in each group and TOR are presented in Fig. 5

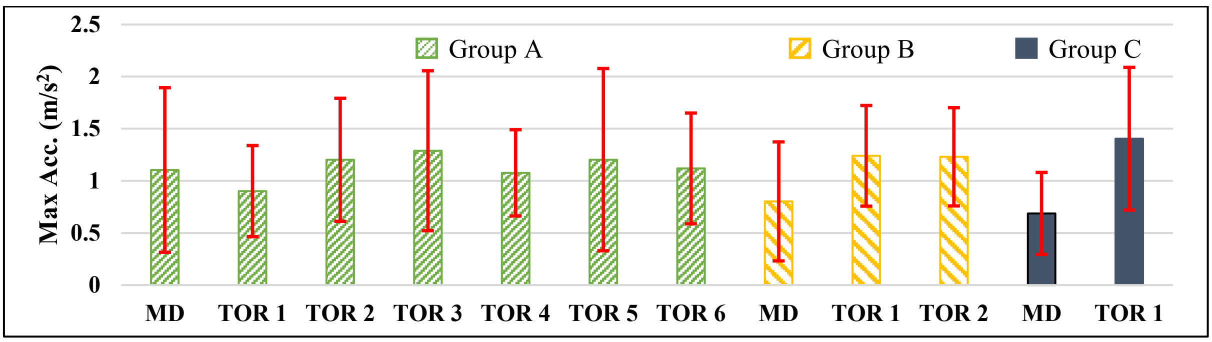


Fig 5. Comparing the means and standard deviations of maximum acceleration between all groups (MD is Manual Driving and TOR is Take-Over Request).

3.3. Maximum Deceleration

Larger deceleration indicates harder brakes and shows risky driving behavior. Safe driving behavior is characterized by deceleration less than 4 m/s^2 (Vaiana et al., 2014). Therefore, analysis of deceleration behavior plays an important role in assessing driving quality. Generally, results showed that maximum deceleration is increased after TOR compared to manual driving. Modeling results showed that the mode of driving has a significant effect on maximum deceleration ($t = 2.61, p = 0.0108$), as the transition from automated to manual driving would increase the maximum deceleration by 70.2%. Results showed that the longer the automated operation, the higher the maximum acceleration. Duration of automated operation showed a significant effect on maximum deceleration in TORs after 5 minutes of HAD ($t = 2.46, p = 0.0103$), 15 minutes of HAD ($t = 3.16, p = 0.0021$), and 30 minutes of HAD ($t = 2.74, p = 0.00719$). Moreover, compared to manual driving, 5 minutes of HAD increases maximum deceleration by 75.7%, and the increment of maximum deceleration for 15 and 30 minutes of HAD is 96.8% and 97.0% respectively. No significant effect was observed for repeated TORs in maximum deceleration. In addition, among driver's characteristics, driver's age and annual mileage showed significant effects considering a HAD driving mode. Compared to drivers with 20-30 years old, drivers who were between 40 to 50 years old had 76.9% and drivers with more than 50 years old 84.3% higher maximum declaration (drivers with 40-50 years old: $t = 1.99, p = 0.0491$ and drivers with more 50 years old $t = 2.01, p = 0.0469$) after TORs. Driver with higher annule driven mileage shoed lower maximum deceleration after TORs. The means and standard deviations of participants' max deceleration are provided in Fig. 6.

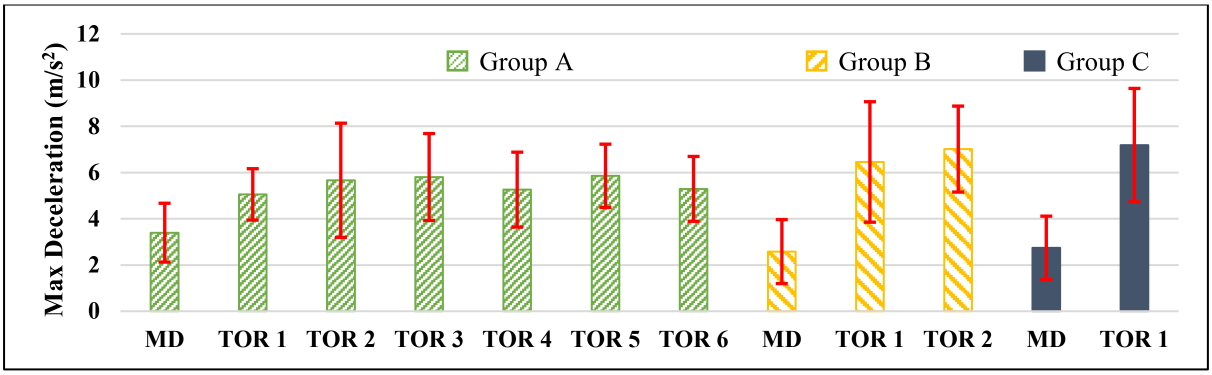


Fig. 6. Comparing the means and standard deviations of maximum deceleration between all groups

3.4. Mean Acceleration

Results showed that the mean of acceleration after TOR is increased compared to manual driving. However, only the duration of automated operation showed a significant effect, where coefficients of 15 minutes of HAD ($t = 2.43, p = 0.01674$) and 30 minutes of HAD ($t = 2.03, p = 0.0448$) were significant. Repeated TORs and the interaction of drive's characteristics and driving mode did not show significant effects on the mean of acceleration.

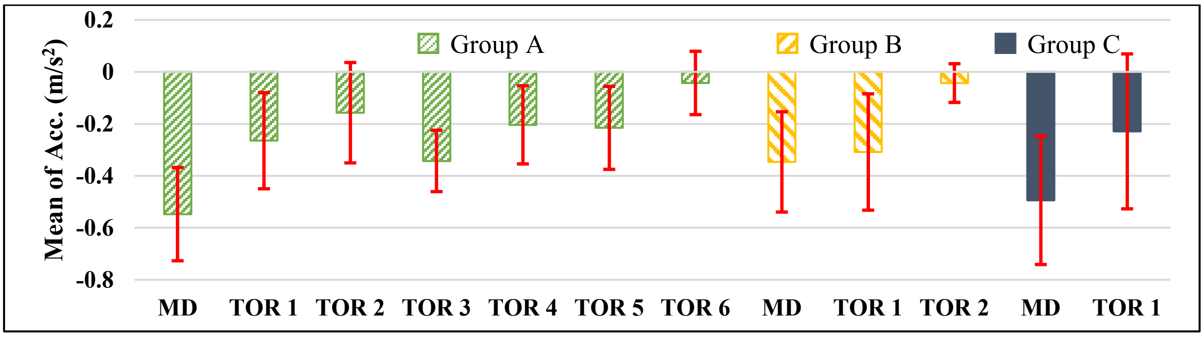


Fig. 7. Comparing the means and standard deviations of the mean of acceleration between all groups

3.5.Maximum Lateral Acceleration

Fig. 8 represents the mean of maximum lateral acceleration for each group. As this figure shows, on average, maximum lateral acceleration increases after the transition from automated to manual driving, and modeling results showed TOR has significant effects on maximum lateral acceleration ($t = 2.21, p = 0.02821$). However, no significant effect was observed for the duration of HAD and repeated TORs. Elasticity analysis showed that maximum lateral acceleration increases by 76.01% after TOR regardless of the duration of HAD and the number of TORs. Moreover, results showed that drivers who had car crashes in their driving history had lower maximum lateral acceleration after TOR. The coefficient of car crashes was significant ($t = 2.21, p = 0.02821$) and results showed that having crashes reduce the maximum lateral acceleration by 41.5% after TOR.

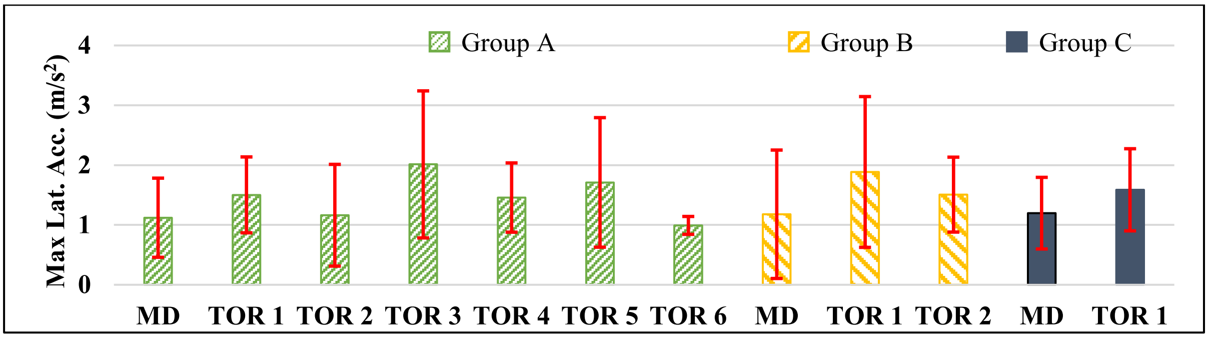


Fig. 8. Comparing the means and standard deviations of maximum lateral acceleration between all groups

3.6. Maximum Heading Error

Heading error shows the angle between the road and the vehicle heading and represents the smoothness of turns. The higher heading error shows intense turn and is risky driving behavior. Modeling maximum heading error showed that, the transition from automated to manual driving has a significant effect on the maximum heading error ($t = 2.81, p = 0.0054$). Results showed that TOR increases the maximum heading error by 89.6%, Which means that drivers had to take more intense turns to bypass the critical event after TOR compare to manual driving. Moreover, drivers with more than 50 years old had higher maximum acceleration ($t = 2.08, p = 0.0398$). Fig. 9 represents the means and standard deviations of maximum heading error in each group. As this figure shows, maximum heading error increases in TOR condition compare to manual driving.

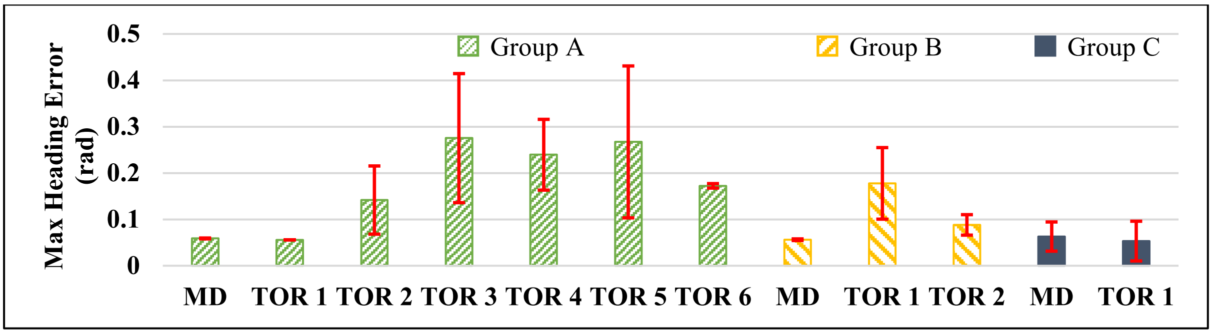


Fig. 9. Comparing the means and standard deviations of maximum deceleration between all groups

3.7. Minimum Headway Distance

Headway distance refers to Headway distance refers to the distance between the vehicle and the front vehicle (bumper to bumper). Results showed that the minimum headway distance had fluctuations after TOR. No significant effect was observed for the effect of TOR. However, modeling results showed that the duration of HAD has significant effects on minimum headway distance where 30 minutes of HAD showed significant effects ($t = -2.07, p = 0.0408$) and caused minimum heading distance to reduce by 16.4%. Moreover, drivers' age showed significant effects where drivers with more than 50 years old will show 18.5% shorter headway distance ($t = -1.98, p = 0.049$) in a TOR condition. No significant effect was observed for repeated TORs. Fig. 10 illustrates the means and the standard deviations of the minimum headway distance for each group.

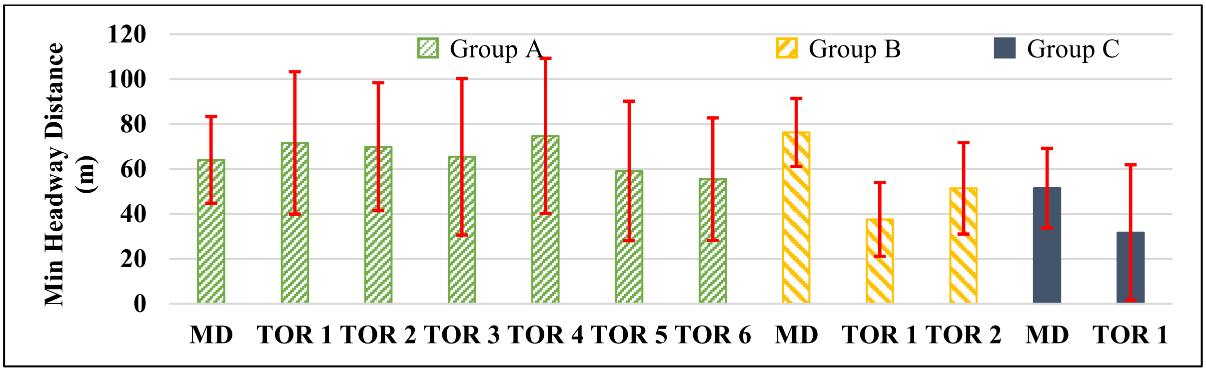


Fig. 10. *Comparing the means and standard deviations of maximum deceleration between all groups*

3.8. Maximum Speed

Analyzing participants' maximum speed showed that, generally, maximum speed reduces after the transition from automated to manual driving. Also, modeling results showed that the effect of driving mode (MD/HAD) is significant ($t = -2.40, p = 0.01729$), and regaining the vehicle control after TOR causes participants' maximum speed reduces by 49.3%. Moreover, repeated TOR showed significant effects. In this regard, the coefficients of second TOR ($t = -1.98, p = 0.049$), the third TOR ($t = -2.47, p = 0.1433$), the fourth TOR ($t = -2.73, p = 0.0068$), and the sixth ($t = -3.15, p = 0.0018$) were significant. Results showed that repeated TOR would reduce drivers' maximum speed. No significant effect was observed for the effect of automated operation duration and driver's characteristics on maximum speed after TORs. The means and the standard deviation of participants' maximum speed in each group are presented in Fig. 11. As this figure shows, participants' maximum speed reduced after TOR compared to MD.

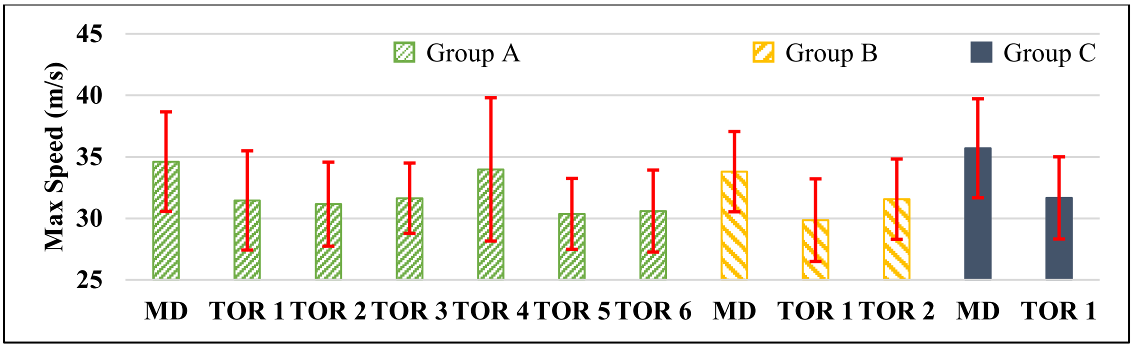


Fig. 11. Comparing the means and standard deviations of maximum speed between all groups

3.9. Minimum Speed

The results for the minimum speed are in line with the maximum speed. Generally, the transition from automated to manual driving most often led to lower minimum speed. Except for the fourth TOR on group A, the minimum speed was reduced after TORs compared to manual driving. Fig. 12 shows the mean and the standard deviation of minimum speed in all groups. As this figure shows, minimum speed reduced significantly after TOR, especially at the sixth TOR of group A. modeling results showed that the effect of driving mode (MD/HAD) is significant on minimum speed ($t = -3.78, p = 0.0002$). Elasticity analysis showed that the transition from automated to manual driving would reduce the minimum speed by 57.6%. Additionally, results showed that repeated TOR has significant effects on minimum speed. However, no significant effects were observed for the duration of automated operation and driver's characteristics.

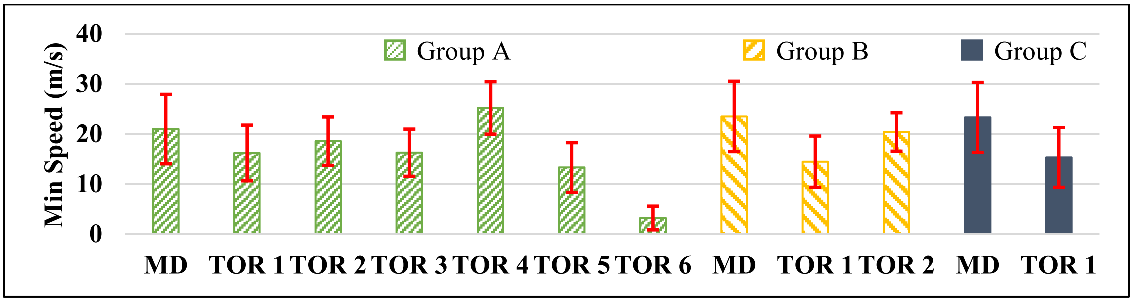


Fig. 12. Comparing the means and standard deviations of minimum speed between all groups

3.10. Maximum Lateral Speed

Maximum lateral speed is a driving behavior index that provides information about participants' lane-changing behavior. Similar to maximum lateral acceleration (section 3.5), results showed that driving mode (MD/HAD) has significant effects on maximum lateral speed ($t = -3.78, p = 0.0002$). Elasticity analysis showed that TOR would increase the maximum lateral speed by 53.1%. Moreover, results showed that driver's age, education, and tickets showed significant effects on maximum lateral speed. The maximum lateral speed reduces in older drivers and more educated drivers had lower maximum lateral speed; While drivers who received tickets in the last two years had higher maximum speed after TOR. Fig. 13 presents the means and the standard deviation of maximum lateral acceleration.

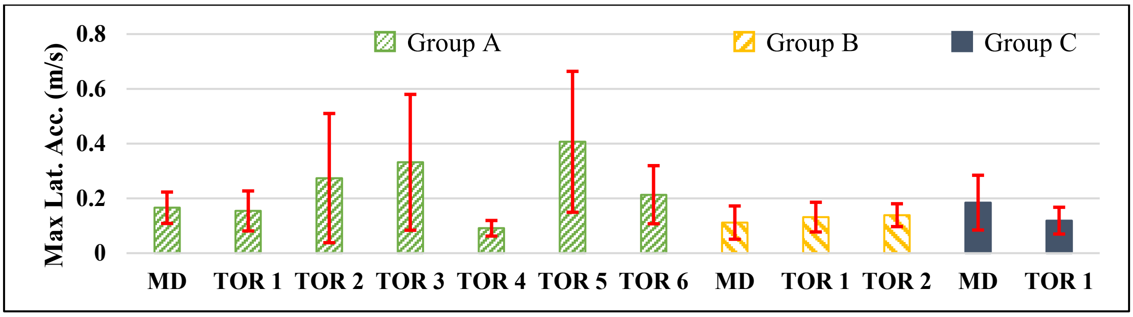


Fig. 13. Comparing the means and standard deviations of maximum lateral speed between all groups

4. Discussion

This study aimed to investigate the effect of TOR on CMV drivers' driving behavior in highly automated vehicles (level 4) and evaluate the effect of repeated TORs, duration of automated operation, and drivers' characteristics. Four hypotheses were assumed in this study and an experiment was designed on a driving simulator for data collecting. The driving behaviors of 45 CMV drivers were collected in bypassing critical events in two driving modes- manual and highly automated driving- and were compared together. Multilevel Mixed Linear Model (MMLM) is applied to test the hypothesis of the study due to the nested structure of data collected.

Hypothesis-1 assumes CMV drivers' driving behavior changes after TORs compared to continuous manual operation. The result of modeling driving behavior indices showed that at least drivers' max deceleration, max lateral acceleration, max heading error, max speed, min speed, and max lateral speed changed in TOR conditions compared to manual driving. Participants' maximum deceleration deteriorated after TORs, where they used higher deceleration (harder brakes) to control the vehicle. Moreover, participants' lateral control (lane changing behavior) was changed, since the maximum heading error, maximum lateral acceleration, and speed increased. Participants showed more risky driving behavior in lateral vehicle control. However, maximum speed and minimum speed were reduced in TOR conditions compared to manual driving. An important point should be discussed here. Since a TOR condition was described as a situation where the system reaches its operation limit (road condition or critical events), in TOR moments participants expected a critical condition while critical events in the manual driving section happened without however preceding alert. This expectation of critical events might have affected the participants driving behavior, although this condition may happen in the real world too. To sum up, the results of this study could approve Hypothesis-1, where significant changes happened after TORs.

Hypothesis-2 claims that CMV drivers' driving behavior depends on the duration of automated operation before transitioning to non-automated operations. The results strongly approved this assumption. CMV drivers' reaction time to TOR, max acceleration, mean of acceleration, and headway distance only changed in long-automated operation. Also, changes in participants' max deceleration and min speed are intensified in longer-automated operations. Moreover, analysis of participants' reaction time to TORs showed that the reaction time will increase significantly in longer automated operations. Therefore, the results of this study approve Hypothesis-2.

Hypothesis-3 assumes that driving behavior would improve after a sequence of TORs (repeated TORs). Results showed that in a repeated TOR scenario, drivers' reaction time will improve. Also, participants could adopt their max and min speed in a repeated TOR scenario. Repeated TOR did not show significant effects on other driving behavior indices; While, based on the literature we expected to observe more significant effects. One reason could be the high occurrence of TORs and short intervals which may have affected the driving behaviors. To sum up, although the few dependent variables were affected by repeated TORs, repeated TORs showed positive effects on all three affected variables. Therefore, it is concluded that repeated TOR would improve driving behavior after TORs.

Finally, Hypothesis-4 assumes that driver's driving behavior after TOR interacts with drivers' characteristics. Results showed that participants' reaction time is highly correlated with the drivers' age. It is predicted that reaction time in drivers older than 50 years increases 43.8% compared to younger drivers (less than 30 years old). Also, although gender showed a significant effect on reaction time, since the population of females was very small, we cannot consider it as concrete evidence of the effectiveness of gender on reaction time (more research is needed in this regard). Moreover, it is predicted that drivers with worse driving history (i.e., more crashes and tickets) will have more risky driving behavior after TORs. Drivers' driving history (tickets or crashes) increased maximum acceleration, max deceleration, and mean of acceleration, max speed, and max lateral speed. Moreover, results showed that CMV drivers who work more (i.e., more annual mileage), are more mentally ready to respond to possible critical events. To sum up, it could be concluded that the results of this study approved the Hypothesis-4.

The finding of this paper showed that similar to previous studies on passenger car drivers (Gibson et al., 2016; Vlakveld et al., 2018; Petersen et al., 2019), CMV drives' driving. behavior deteriorated after the transition from automated to manual driving in highly automated vehicles. However, it is expected that CMV drivers perform better after TOR due to more driving experience and the dependency of their career on their driving behavior. Wright, Samuel, Borowsky, Zilberstein, and Fisher (2016) showed that experienced drivers have a better performance after TOR and gain proper situation awareness quicker.

In terms of assessing the effect of automated operation duration before TOR, the findings of this research contradict the results of (Feldhütter et al., 2017) who did not find evidence of the effect of automated operation duration on driving quality. However, our results are in line with the results of (Bourrelly et al., 2019) who showed that the long-automated phase significantly affects reaction time and driving behavior. A source of these changes could be drivers' fatigue and drowsiness as previously found by (Graw et al., 2004), longer reaction times may indicate a decrease in the level of consciousness and an increase in fatigue. Moreover, Vogelpohl et al (2018) revealed that that driving without non-driving-related tasks increases fatigue and drowsiness during extended periods in automated driving. A solution could be asking drivers to regain vehicle control after 15-20 minutes of automated operation to avoid increate of fatigue, drowsiness and regaining situation awareness.

The current study considers a fixed budget time in the designed experiment, however, the finding approved the finding of (Vlakveld et al., 2018) who found that drivers needed at least six seconds of budget time to regain the vehicle control. Therefore, automotive companies should consider that if highly automated vehicles could not predict the critical event six seconds before, the chance of collision and severe crashes increases significantly. In addition, the implementation of highly automated commercial vehicle fleet necessitates reviewing the effect of different budget times in long-automated phases. Since long-automated driving significantly increases the reaction time to TOR, it seems crucial to investigate the effect of time budget on driver's performance in long-automated driving scenarios, the issue that is not addressed in the literature.

Moreover, it is suggested that companies that are planning to recruit drivers for their automated vehicle fleets should consider younger drives and drivers with a clean driving background in priority for the first phase of implementing highly automated commercial vehicles. This research provided evidence to show that older CMV drivers will have a longer reaction time to the TOR. This finding is in line with the finding of (Li et al., 2018). Moreover, the driving behavior of drivers with traffic accidents in their driving history was affected by TOR significantly. We hope that by addressing the CMV drivers' driving behavior after TOR in long-automated driving and repeated TOR conditions, the field of transition research may come closer to realizing the benefits of automated driving technologies and ensure the automotive future is as bright as has been promised.

4.1. Limitations

Some limitations of the present study should be acknowledged. First, because the experiment was conducted using a driving simulator, it is difficult to determine if the same results would be shown in a real vehicle. Moreover, the simulator used in this study is a low fidelity driving simulator with limitations in simulating the real world. For instance, the RDS-500 does not provide side views very well therefore drivers' lane changing, and turns could be affected by the lack of proper side views. Although RDS-500 uses robust software, users cannot sense the speed at higher speeds. To overcome this problem, we asked our participants to constantly check their speed with the speedometer, but this problem still might have affected the results.

Second, in the designed scenario for the repeated TOR, the high frequency of TORs and the short interval between each occurrence might have affected the results in this section. It is suggested that future studies consider longer time intervals.

Third, one of the effective parameters in drivers' driving behavior is the ambient traffic. In this study, the ambient traffic provided by the driving simulator was not constant and low fluctuations could be observed during the experiment. Therefore, the ambient traffic during the

TORs/critical event may not be completely the same. Hence, participants driving behavior could be affected by this problem.

Finally, the study tried to rule out the effect of non-driving related tasks or any distraction. However, since the experiment was not conducted in an isolated environment, participants may have been distracted in some cases and this could have affected the results and the data.

4.2. Future works

This study did not consider the effect of engaging in non-driving related tasks during the automated operation. Future studies can evaluate the effect of engaging in non-driving related tasks in long automated operation conditions. Moreover, future studies can consider different measures, such as eye movements, body movement, brake patterns, to evaluate the effect of long automated driving on TOR conditions. Driving under time pressure is another source of interest that future studies can follow.

5. Conclusion

Commercial Motor vehicle (CMV) drivers' mistakes were the leading cause of CMV involved crashes (Federal Motor Carrier Safety Administration, 2006) and the introduction of automated vehicles has the potential to reduce CMV crashes and associated social costs. At present, several companies have been developing and demonstrating the level 3 and level 4 of automated CMVs, investigation of driver behavior is critical to developing engineering countermeasures. In level 4 automated vehicles, even though the system is responsible for longitudinal and lateral control of vehicle and drivers can engage in other tasks (instead of monitoring driving performance), when the system reaches its maximum operational capabilities (because of roadway conditions, crashes, or system failures), the driver will be sent a TOR. In this condition, drivers need to regain vehicle control and drive manually to bypass the system's operational limitations. This transition from automated to manual affects drivers' driving behavior. The first objective of this paper was to investigate the changes in driving behavior of CMV drivers after Take-Over Requests. In this regard, an experiment was designed using a driving simulator and CMV drivers' responses to critical events in automated operation compared with their continuous manual driving. Results showed reaction time and driving behavior will be affected by TOR conditions. The other objective of this paper was to investigate the effect of automated driving duration. This research showed that a 30-minute automated driving increases the reaction time to TOR significantly and intensifies the effect of TOR on driving behavior, especially in lateral control and maximum deceleration. This research suggested that dividing long-automated driving into a shorter segment could improve driver behavior and result in safer responses to critical events. Moreover, this paper should that drivers' reaction time and some driving behavior indices would improve in a repeated TOR scenario. Finally, this research investigated the interaction of drivers' characteristics (e.g., age, driving experience, and driving history) and their performance after the transition from automated to manual driving. Results showed that regardless of the duration of automated operation and the number of TORs, the driving performances of older drivers and drivers with crashes in their driving history will be more affected by TORs.

Appendix

Appendix A: *Results from the Multilevel Mixed Linear Model for all dependent variables. For each predictor, beta coefficients are given with t-value in parentheses.*

Fixed effects	Log (Dependent variable)						
	Reaction Time	Max. Acc.	Max. Dec.	Mean Acc.	Max. Lat. Acc	Max. HE	Min. HD
(Intercept)	.417 (.965)	-.824 (-.97)	1.494 (.85)	-.755 (-1.58)	-1.456 (-1.75)	-3.68(-4.48) ***	4.325 (3.63) **
Gender (Reference: Female)							
Male	--	.035 (.08)	.369 (.43)	-.042 (-.16)	.214 (.51)	.359 (.87)	-1.373 (-2.29) *
Age (Reference: 20-30 years old)							
30 to 40 years old	--	-.697 (-1.92)	1.20 (1.13)	.124 (.53)	.578 (1.43)	.381 (.95)	.462 (.79)
40 to 50 years old	--	-.487 (-.93)	2.98 (2.77) **	-.223 (-.61)	-.033 (-.05)	-.396 (-.63)	.086 (.09)
> 50 years old	--	-.378 (-.52)	4.1 (3.83) ***	-.186 (-.44)	.107 (.14)	-.225 (-.31)	.109 (.10)
Education (Reference: high school or less)							
College Degree	--	-.333 (-.65)	2.388 (2.26) *	.225 (.81)	.596 (1.23)	.17 (.354)	.151 (.22)
Associate degree	--	.057 (.13)	2.224 (2.38) *	.253 (1.05)	.766 (1.84)	.474 (1.143)	.416 (.69)
Bachelor's degree or higher	--	-.051 (-.12)	2.19 (2.47) *	-.003 (-.01)	.634 (1.54)	.458 (1.12)	-.16 (-.27)
Crash (Reference: No)							
Yes	--	.299 (1.19)	1.43 (2.75) **	-.436 (-2.84) **	-.053 (-.19)	-.147 (-.56)	-.101 (-.26)
Tickets (Reference: No)							
Yes	--	-.027 (-.11)	-.599 (-1.13)	.374 (2.44) *	.439 (1.65)	.196 (.743)	.443 (1.16)
Annual Mileage							
20,000 to 25,000	--	-.382 (-1.13)	.135 (.19)	.373 (1.61)	-.391 (-.97)	-.747 (-1.88)	1.775 (3.08)
25,000 to 30,000	--	-.674 (-1.59)	-.97 (-1.08)	.19 (.71)	-.99 (-2.11)	-1.035 (-2.21) *	1.829 (2.70)
> 30,000 km	--	-1.199 (-3.14)	-1.265 (-1.58)	.3 (1.24)	-.68 (-1.62)	-.806 (-1.94)	1.51 (2.51)
Driving Mode (Reference: Manual Driving)							
Automated Driving (HAD)	--	.143 (.08)	1.21 (3.78) ***	.375 (.54)	2.307 (2.21) *	2.262 (2.81) *	.879 (1.368)
Automated Operation Duration (Reference: No HAD)							
5 Minutes of HAD	--	1.171 (1.08)	2.144 (2.46) **	.429 (1.72)	.105 (.38)	.094 (.34)	.756 (1.82)
15 Minute of HAD	.291 (2.02) *	1.684 (1.77)	3.432 (3.19) **	.515 (2.43) *	.351 (.96)	.686 (1.74)	-.631 (-1.06)
30 Minute of HAD	.388 (2.68) **	1.84 (2.61) **	3.521 (2.74) **	.412 (2.03) *	.244 (.59)	.132 (.29)	-.98 (-2.07) *

$* \ p < .05$, $** \ p < .01$, and $*** \ p < .001$

Appendix A (Continued)

Fixed effects	Dependent variable						
	Reaction Time	Max. Acc.	Max. Dec.	Mean Acc.	Max. Lat. Acc	Max. HE	Min. HD.
Num. of TOR (Reference: No HAD)							
One TOR	--	-.526 (-.88)	-.129 (-.11)	-.314 (-1.69)	.138 (.44)	-.004 (-.01)	-.689 (-1.38)
Two TORs	-.244 (-3.71) ***	-.529 (-1.24)	.428 (.53)	-.033 (-.18)	-.002 (-.06)	-.179 (-.52)	-.443 (-.89)
Three TORs	-.192 (-2.21) *	.125 (.29)	.661 (.82)	-.309 (-1.56)	.418 (1.25)	.749 (2.06) *	.114 (.25)
Four TORs	-.147 (-1.69)	-.1 (-.23)	.114 (.14)	-.17 (-.86)	.192 (.57)	.293 (.81)	.089 (.17)
Five TORs	-.256 (-2.95) **	.285 (.67)	.711 (.87)	-.382 (-1.62)	-.042 (-.13)	.309 (.85)	-.724 (-1.37)
Six TORs	-.392 (-4.51) ***	.301(.81)	.598 (.62)	-.278 (-.141)	-.154 (-.26)	.418 (.92)	.699 (1.67)
HAD. Duration × Num. of TOR							
5 Minutes of HAD × One TOR	--	.436 (.74)	1.222 (1.09)	.05 (.24)	-.007 (-.02)	.083 (.23)	-.487 (-.93)
5 Minutes of HAD × Two TOR	-.225 (-2.42) *	-.177 (-.40)	.951 (1.14)	.211 (1.03)	-.538 (-1.61)	-.37 (-1.03)	.075 (.14)
5 Minutes of HAD × Three TOR	-.183 (-1.97) *	-.615 (-1.39)	1.183 (1.42)	-.005 (-.03)	.077 (.23)	.697 (1.93)	.474 (.91)
5 Minutes of HAD × Four TOR	-.137 (-1.47)	.039 (.09)	.637 (.76)	.134 (.65)	-.149 (-.44)	.241 (.67)	.448 (.86)
5 Minutes of HAD × Five TOR	-.247 (-2.65) **	-.186 (-.42)	1.234 (1.48)	-.078 (-.38)	-.383 (-1.14)	.257 (.71)	-1.267 (-2.22) *
5 Minutes of HAD × Six TOR	-.382 (-4.11) ***	.199 (.45)	.485 (.58)	.305 (1.47)	-.339 (-1.01)	-.058 (-.16)	-.364 (-.69)
15 Minutes of HAD × One TOR	.301 (2.03) *	-.086 (-.19)	.979 (1.07)	.017 (.08)	-.363 (-.99)	.047 (.12)	-1.195 (-2.09) *
15 Minutes of HAD × Two TOR	.144 (.91)	-.091 (-.18)	1.536 (1.68)	.418 (1.86)	-.113 (-.31)	.149 (.38)	-.391 (-.74)
30 Minutes of HAD × One TOR	.388 (2.68) **	1.84 (2.61) **	3.521 (2.74) **	.412 (2.03) *	.244 (.59)	.132 (.29)	-.98 (-2.07) *
Driving Mode × Driver Factor							
HAD × Male	.474 (2.34) *	.781 (.89)	.091 (.06)	.137 (.42)	-.368 (-.66)	-.747 (-1.27)	-.574 (-.68)
HAD × 30 to 40 years old	.387 (1.971) *	-.728 (-.89)	.864 (.92)	-.176 (-.58)	-.607 (-1.18)	1.016 (1.32)	-1.152 (-1.47)
HAD × 40 to 50 years old	.097 (.33)	-1.321 (-1.04)	1.465 (1.99) *	.032 (.07)	-.034 (-.04)	1.518 (1.88)	-1.571 (-1.35)
HAD × > 50 years old	.576 (2.05) *	-.593 (-.38)	1.849 (2.01) *	.185 (.32)	.085 (.09)	1.733 (2.08) *	-2.951 (-1.98) *
HAD × Edu2	-.226 (-.91)	.427 (.40)	1.618 (1.07)	-.06 (-.15)	-1.013 (-1.19)	-1.077 (-1.50)	-2.161 (-2.08) *
HAD × Edu3	-.067 (-.32)	.653 (.69)	1.207 (1.45)	-.09 (-.26)	-1.139 (-1.28)	-.891 (-1.42)	-1.859 (-2.05) *
HAD × Edu4	.164 (.81)	-.268 (-.29)	.914 (.62)	-.041 (-.12)	-.972 (-1.132)	-.87 (-1.45)	-1.125 (-1.29)
HAD × Crash	.054 (.42)	-.267 (-.48)	-.775 (-.86)	.266 (1.31)	-1.642 (-2.06) *	-.23 (-.63)	.584 (1.11)
HAD × Tickets	.188 (1.61)	.041 (.07)	1.07 (1.19)	-.044 (-.22)	-.52 (-1.51)	-.434 (-1.21)	-1.306 (-2.49) *
HAD × 15,000 to 20,000 km	-.214 (-1.16)	1.11 (1.37)	4.68(3.66) ***	-.37 (-1.29)	.637 (1.31)	1.042 (1.93)	-.949 (-1.28)
HAD × 20,000 to 25,000 km	-.241 (-1.19)	.583 (.59)	2.962 (2.29) *	-.326 (-.94)	.481 (1.04)	1.721 (1.85)	-1.492 (-1.65)
HAD × > 25,000 km	-.213 (-1.08)	.856 (.99)	2.204 (1.19)	-.58 (-1.85)	.267 (.88)	.965 (1.81)	-.931 (-1.14)

$* \ p < .05$, ** $p < .01$, and *** $p < .001$

Appendix A (Continued)

Fixed effects	Dependent variable					
	Min. TTC	SDLP	Max. Speed	Min. Speed	Mean Speed	Max. Lat. Speed
(Intercept)	1.482 (1.32)	-1.28 (-2.15) *	3.43 (7.04) *	1.36 (1.38)	2.12 (6.92) ***	-4.01(-4.64) ***
Gender (Reference: Female)						
Male	-1.251 (-2.21) *	.20 (.67)	.033 (.81)	.147 (.29)	.028 (.29)	.363 (.83)
Age (Reference: 20-30 years old)						
30 to 40 years old	.598 (1.09)	.289 (.99)	.011 (.27)	.424 (.89)	.012 (.13)	.305 (.72)
40 to 50 years old	.375 (.44)	-.338 (-.75)	-.029 (-.46)	-.296 (-.39)	-.168 (-1.19)	-.442 (-.67)
> 50 years old	.251 (.25)	-.171 (-.32)	-.054 (-.75)	-.072 (-.08)	-.123 (-.75)	-.003 (-.01)
Education (Reference: high school or less)						
College Degree	.004 (.01)	.242 (.7)	-.012 (-.26)	.637 (1.12)	.116 (1.074)	.738 (1.47)
Associate degree	.145 (.25)	.339 (1.13)	-.015 (-.38)	.563 (1.14)	.106 (1.137)	.977 (2.25) *
Bachelor's degree or higher	-.291 (-.52)	.11 (.37)	.003 (.07)	.34 (.69)	.039 (.42)	.945 (2.21) *
Crash (Reference: No)						
Yes	.07 (.194)	-.325 (-1.71)	.033 (1.27)	-.667 (-2.12) *	-.104 (-1.75)	-.074 (-.27)
Tickets (Reference: No)						
Yes	.157 (.44)	.473 (2.49) *	.063 (2.42) *	.725 (2.31) *	.197 (3.33) **	.53 (1.92)
Annual Mileage						
20,000 to 25,000	1.31 (2.42) *	.027 (.094)	-.024 (-.62)	.945 (2.01) *	.155 (1.73)	.006 (.01)
25,000 to 30,000	1.423 (2.23) *	-.257 (-.76)	-.071 (-1.55)	.358 (.64)	.044 (.41)	-.66 (-1.35)
> 30,000 km	1.094 (1.93)	-.08 (-.28)	-.029 (-.72)	.796 (1.61)	.115 (1.23)	-.439 (-1.01)
Driving Mode (Reference: Manual Driving)						
Automated Driving (HAD)	1.147 (1.44)	.446 (.56)	-.181 (-2.40) *	-1.9 (-3.78) ***	.322 (1.22)	1.105 (2.84) **
Automated Operation Duration (Reference: No HAD)	.648 (1.68)	-.03 (-.17)	-.05 (-1.58)	-1.7 (-5.163) ***	-.069 (-1.16)	.074 (.26)
5 Minutes of HAD	.701 (1.51)	.362 (1.56)	-.038 (-.95)	-1.43 (-3.25) **	-.056 (-.70)	.219 (.61)
15 Minute of HAD	.76 (1.27)	.17 (.64)	-.017 (-.39)	-1.91 (-3.78) ***	-.066 (-.72)	-.07 (-.18)
30 Minute of HAD						

$* \ p < .05$, ** $p < .01$, and *** $p < .001$

Appendix A (Continued)

Fixed effects	Dependent variable					
	Min. TTC	SDLP	Max. Speed	Min. Speed	Mean Speed	Max. Lat. Speed
Num. of TOR (Reference: No HAD)						
One TOR	-.571 (-1.24)	-.212 (-1.06)	-.34 (-1.02)	-1.37 (-2.56) *	-.089 (-1.28)	-.074 (-.26)
Two TORs	-.441 (-.96)	-.237 (-1.18)	-.59 (-1.98) *	-1.76 (-2.58) *	-.017 (-.25)	-.075 (-.26)
Three TORs	.206 (.42)	-.14 (-.66)	-.83 (-2.47) *	-1.54 (-2.75) **	-.108 (-1.46)	.161 (.53)
Four TORs	.104 (.21)	.097 (.45)	-.92 (-2.73) **	-2.04 (-2.98) **	-.048 (-.65)	.045 (.15)
Five TORs	-.526 (-1.07)	-.02 (-.09)	-.31 (-1.01)	-1.26 (-2.08) *	-.16 (-2.17) *	-.211 (-.71)
Six TORs	.602 (1.54)	.007 (.04)	-.99 (-3.15) **	-1.68 (-3.10) **	-.067 (-1.14)	.912 (.33)
HAD. Duration × Num. of TOR						
5 Minutes of HAD × One TOR	-.506 (-1.03)	.033 (.15)	-.046 (-1.25)	-.178 (-1.55)	.311 (1.31)	.439 (1.64)
5 Minutes of HAD × Two TOR	.058 (.12)	-.452 (-2.12) *	-.023 (-.63)	-.098 (-1.30)	.323 (1.36)	-.092 (-.34)
5 Minutes of HAD × Three TOR	.488 (.99)	-.125 (-.59)	-.038 (-1.03)	-.165 (-1.51)	.266 (1.12)	.524 (1.98) *
5 Minutes of HAD × Four TOR	.386 (.79)	.112 (.52)	.010 (.27)	-.34 (-2.06) *	.322 (1.36)	.297 (1.11)
5 Minutes of HAD × Five TOR	-.243 (-.49)	-.005 (-.02)	-.047 (-1.28)	-.44 (-2.37) **	.218 (.92)	.063 (.24)
5 Minutes of HAD × Six TOR	.303 (.61)	.009 (.04)	.045 (1.21)	-.71 (-3.18) ***	.368 (1.54)	.106 (.38)
15 Minutes of HAD × One TOR	-.92 (-1.72)	-.147 (-.63)	-.066 (-1.62)	-.222 (-.68)	.255 (1.12)	.293 (1.07)
15 Minutes of HAD × Two TOR	-1.125 (-2.29) *	.289 (1.24)	-.009 (-.23)	-.484 (-1.97) *	.375 (1.65)	.542 (1.98)
30 Minutes of HAD × One TOR	.76 (1.27)	.17 (.64)	-.017 (-.39)	-.537 (-1.96)	-.066 (-.72)	-.07 (-.18)
Driving Mode × Driver Factor						
HAD × Male	-.447 (-.56)	-.11 (-.29)	-.024 (-.40)	-.133 (-.19)	-.029 (-.24)	-.504 (-.96)
HAD × 30 to 40 years old	-1.204 (-1.63)	-.341 (-.98)	-.103 (-1.83)	-.549 (-.87)	-.077 (-.67)	-1.544 (-2.24) *
HAD × 40 to 50 years old	-1.835 (-1.68)	.159 (.31)	-.127 (-1.52)	.102 (.11)	.019 (.11)	-2.14 (-3.24) **
HAD × > 50 years old	-3.056 (-2.18) *	.288 (.44)	-.152 (-1.43)	.354 (.29)	-.019 (-.08)	-2.55 (-3.29) **
HAD × Edu2	-1.823 (-1.87)	-.301 (-.66)	-.08 (-1.09)	-.533 (-.64)	-.184 (-1.22)	-1.891 (-2.96) *
HAD × Edu3	-1.433 (-1.68)	-.292 (-.74)	-.055 (-.86)	-.384 (-.53)	-.177 (-1.34)	-1.78 (-3.19) **
HAD × Edu4	-.806 (-.98)	-.304 (-.80)	-.095 (-1.55)	-.154 (-.22)	-.12 (-.95)	-1.75 (-3.29) **
HAD × Crash	.333 (.672)	.265 (1.14)	-.061 (-1.63)	.283 (.67)	-.012 (-.15)	-.39 (-1.19)
HAD × Tickets	-1.119 (-2.26) *	-.253 (-1.09)	-.103 (-2.7)	-.236 (-.56)	-.164 (-2.13)	.73 (2.24) *
HAD × 15,000 to 20,000 km	-.638 (-.913)	-.041 (-.12)	-.027 (-.52)	-.84 (-1.40)	-.129 (-1.18)	-.273 (-.59)
HAD × 20,000 to 25,000 km	-1.141 (-1.34)	.218 (.54)	-.002 (-.03)	-.301 (-.41)	-.02 (-.15)	.694 (1.24)
HAD × > 25,000 km	-.439 (-.57)	-.186 (-.52)	-.015 (-.26)	-.916 (-1.40)	-.086 (-.73)	.12 (.24)

$* \ p < .05$, $** \ p < .01$, and $*** \ p < .001$

Appendix B. Elasticity effects of the Multilevel Mixed Linear Model for all dependent variables (percentage).

Variable	RT	Max. Acc.	Max. Dec.	Mean Acc.	Max. L. Acc.	Max. HE.	Min. HD.	Min. TTC	SDLP	Max. Sp.	Min. Sp.	Mean Sp.	Max. L. Sp.
Automated Driving (HAD)		13.3	70.2	31.3	76.0	89.6	58.5	68.2	36.0	-49.3	-57.6	27.5	53.1
5 Minutes of HAD		69.0	75.7	34.9	10.0	9.0	53.0	47.7	-3.0	-5.1	-22.6	-7.1	7.1
15 Minute of HAD	25.2	81.4	96.8	40.2	29.6	49.6	-87.9	50.4	30.4	-3.9	-39.4	-5.8	19.7
30 Minute of HAD	32.2	84.1	97.0	33.8	21.7	12.4	-16.4	53.2	15.6	-1.7	-22.3	-6.8	-7.3
One TOR		-69.2	-13.8	-36.9	12.9	-0.4	-65.2	-77.0	-23.6	-40.5	-77.2	-9.3	-7.7
Two TORs	-27.6	-69.7	34.8	-3.4	-0.2	-19.6	-55.7	-55.4	-26.7	-51a.4	-19.6	-1.7	-7.8
Three TORs	-21.2	11.8	48.4	-36.2	34.2	52.7	10.8	18.6	-15.0	-19.3	-49.5	-11.4	14.9
Four TORs	-15.8	-10.5	10.8	-18.5	17.5	25.4	8.5	9.9	9.2	-15.9	-20.8	-4.9	4.4
Five TORs	-29.2	24.8	50.9	-46.5	-4.3	26.6	-16.3	-69.2	-2.0	-36.3	-97.0	-17.4	-23.5
Six TORs	-48.0	26.0	45.0	-32.0	-16.6	34.2	50.3	45.2	0.7	-16.1	-15.5	-6.9	59.8
5 Min of HAD × One TOR		35.3	70.5	4.9	-0.7	8.0	-62.7	-65.9	3.2	-4.7	-24.6	26.7	35.5
5 Min of HAD × Two TOR	-25.2	-19.4	61.4	19.0	-71.3	-44.8	7.2	5.6	-57.1	-2.3	-30.4	27.6	-9.6
5 Min of HAD × Three TOR	-20.1	-85.0	69.4	-0.5	7.4	50.2	37.7	38.6	-13.3	-3.9	25.6	23.4	40.8
5 Min of HAD × Four TOR	-14.7	3.8	47.1	12.5	-16.1	21.4	36.1	32.0	10.6	1.0	-40.0	27.5	25.7
5 Min of HAD × Five TOR	-28.0	-20.4	70.9	-8.1	-46.7	22.7	-25.0	-27.5	-0.5	-4.8	-2.1	19.6	6.1
5 Min of HAD × Six TOR	-46.5	18.0	38.4	26.3	-40.4	-6.0	-43.9	26.1	0.9	4.4	-50.6	30.8	10.1
15 Min of HAD × One TOR	26.0	-9.0	62.4	1.7	-43.8	4.6	-32.4	-15.9	-15.8	-6.8	-12.1	22.5	25.4
15 Min of HAD × Two TOR	13.4	-9.5	78.5	34.2	-12.0	13.8	-23.4	-20.0	25.1	-0.9	-56.6	31.3	41.8
30 Min of HAD × One TOR	32.2	84.1	97.0	33.8	21.7	12.4	-16.4	53.2	15.6	-1.7	-22.3	-6.8	-7.3
HAD × Male	37.7	54.2	8.7	12.8	-44.5	-111.1	-77.5	-56.4	-11.6	-2.4	-14.2	-2.9	-65.5
HAD × 30 to 40 years old	32.1	-17.1	57.9	-19.2	-83.5	63.8	-21.5	-23.3	-40.6	-10.8	-73.2	-8.0	-36.3
HAD × 40 to 50 years old	9.2	-24.7	76.9	3.1	-3.5	78.1	-38.1	-52.5	14.7	-13.5	9.7	1.9	-54.9
HAD × > 50 years old	43.8	-80.9	84.3	16.9	8.1	82.3	-18.5	-20.2	25.0	-16.4	29.8	-1.9	-11.7
HAD × Edu2	-25.4	34.8	80.2	-6.2	-17.4	-19.6	-76.0	-51.0	-35.1	-8.3	-70.4	-20.2	-56.6
HAD × Edu3	-6.9	48.0	70.1	-9.4	-21.4	-14.8	-54.7	-31.1	-33.9	-5.7	-46.8	-19.4	-49.0
HAD × Edu4	15.1	-30.7	59.9	-4.2	-16.3	-13.7	-20.0	-12.9	-35.5	-10.0	-16.6	-12.7	-47.5
HAD × Crash	5.3	-30.6	-117.1	23.4	-41.6	-25.9	44.2	28.3	23.3	-6.3	24.6	-1.2	-47.7
HAD × Tickets	17.1	4.0	65.7	-4.5	-68.2	-54.3	-26.1	-20.2	-28.8	-10.8	-26.6	-17.8	17.5
HAD × 15,000 to 20,000 km	-23.9	67.0	99.1	-44.8	47.1	64.7	-15.3	-89.3	-4.2	-2.7	-131.6	-13.8	-31.4
HAD × 20,000 to 25,000 km	-27.3	44.2	94.8	-38.5	38.2	82.1	-34.6	-213.0	19.6	-0.2	-35.1	-2.0	50.0
HAD × > 25,000 km	-23.7	57.5	89.0	-78.6	23.4	61.9	-15.7	-55.1	-20.4	-1.5	-149.9	-9.0	11.3

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