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Examining the Takeover Process for Senior Drivers in Conditionally Automated Vehicles

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Abstract

While the consensus suggests that autonomous control is particularly advantageous for older drivers due to reduced driving workload, the challenges brought on by the takeover process may impose additional burdens on this cohort. This study aims to explore the takeover time and takeover quality of older drivers, examining how different driving conditions affect their performance compared to young and middle-aged drivers. By doing so, it seeks to pinpoint potential risks specific to this demographic segment. Seventy-two participants from three age groups— younger, middle-aged, and older drivers—were recruited, each completing eight takeover scenarios. This study addresses a gap in age-related takeover studies, which predominantly target young-old age drivers (65-74 years old), by focusing specifically on the old-old age group (75 + years old) characterized by heightened cognitive impairments. The result revealed that older drivers have significantly higher takeover time and lower takeover quality compared to younger and middle-aged groups. Older drivers exhibited greater use of acceleration and brake more frequently after takeover, and they had significantly higher lateral drifting. Furthermore, the non-driving related tasks distract older drivers more compared to drivers from other age groups. Highway and local roads, as well as curved and straight roads, affect drivers across all age groups similarly. The findings suggest that older drivers encounter enhanced challenges during the takeover process, particularly when non-driving-related tasks were presented during the automation control. Although automation provides convenience to older people, attention should be directed towards mitigating the additional risks associated with takeovers. This conclusion contributes valuable insights for the future customized design of takeover requests tailored to older drivers.

Keywords – Takeover time, takeover quality, conditionally automated driving, older driver.

1. Introduction

From simply maintaining speed to navigating roads all on its own, automated driving has come a long way in changing the way we drive. Throughout this progression, the automation control system takes over more and more of the driving duties. The automation control system can provide transportation to people or goods from one place to another with minimum intervention from human drivers. This provides a potential opportunity for people who exhibit diminished cognitive ability or heightened susceptibility to fatigue, such as older drivers. The automated driving system can offer a great opportunity to improve road safety and handle daily driving tasks for older people [20].

The J3016 standard (SAE J3016™ Recommended Practice: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles) elucidates six levels of automation [22], where level zero is no driving automation and level 5 is fully automation control. The framework has become a foundation in driving automation research, extensively referenced and applied across various studies. The current study focused on level 3 driving automation, referred to as Conditional Driving Automation. At this level, an Automated Driving System (ADS) handles the entire dynamic driving task (DDT) within predefined operational design domains (ODDs), while recognizing the presence of a user prepared to intervene and respond to requests from the ADS [21]. The process from autonomous control to manual control is the takeover process, initiated by the takeover request (TOR). The takeover process occurs when the driving scenario exceeds its ODD, such as ambiguous road conditions or the presence of hazards along the intended driving trajectory. The system will issue a TOR, which necessitates human intervention. Given that full automation control remains distant, it is crucial to investigate how human drivers interact with automated systems to enhance the safety and efficiency of semi-automated systems.

The TOR is usually delivered in visual, audio, or haptic modality to remind the driver to act. Within the context of conditional driving vehicles, the driver may engage in various non-driving-related tasks (NDRTs) [17] while the vehicle operates in automated driving mode, thereby relinquishing direct supervision of the driving task. The

TOR operates as an alert to redirect their attention back to the surrounding situation and manual driving task. The driving automation system issues the TOR owing to its recognition of an imminent encounter with situations exceeding its ODD in the near future. Consequently, it requires a human driver to take over the driving task before the system limit is reached. After perceiving the TOR, drivers are expected to take over the vehicle and do manual driving immediately.

A substantial amount of research work was dedicated to investigating the takeover process in the level 3 conditional autonomous vehicles. Collectively, these research works aimed at studying different factors that affect the drivers' takeover behaviors and intend to explore the possibility of improving drivers' performance. This is pursued through the manipulation of takeover settings, such as takeover time, TOR modality, distinct NDRT, and diverse driving conditions. Factors that could influence the takeover performance have been categorized into two distinct types, objective and subjective. The objective factors pertain to the inherent properties of the driving situation or automation system itself, whereas subjective factors are associated with the drivers' individual characteristics and adaptation to the conditional autonomation system [15]. As for the objective factors, time budget is one of the most important factors that affect the takeover behavior. Gold et al. have conducted a comparative study of drivers' behaviors across 5 seconds TOR time and 7 seconds TOR time [3]. The result reveals that drivers become more likely to employ accelerator and brake inputs in situations with abbreviated decision-making intervals, indicative of shorter TOR times. Also, the road condition has a great impact on the takeover process. It has been well acknowledged that curved roads contribute to more crashes compared to straight roads, with the sharper bends exacerbating the situation [16]. The modality of TOR also yields various impacts. Visual modality can convey more complex information, such as speed, RPM, and fuel level and it is easier to interpret. Auditory and haptic alerts can be detected without the driver's eye movement.

Compared to the objective factors, subjective factors affect takeover behaviors from the driver side, such as drivers' experience, age, and cognitive ability. Previous research found that drivers' previous driving experience, including licensed years and annual kilometers, is highly correlated with their takeover performance [26]. Moreover, prior familiarization with automated vehicles also had a positive effect on drivers' performance when they first contacted with the takeover situation [4]. While driving experience positively influences the driver's takeover process, it also has a close relationship with age, which sometimes causes other effects. Horswill et al. found that older drivers need more time to perceive hazards, and this result could be accounted for less contrast sensitivity and useful field of view [5]. Huang and Pitts found that older drivers with higher exercise frequency demonstrated shorter decision-making time in the takeover process of a semi-autonomous vehicle. Also, they stated that the benefit of exercise is more predominant in older drivers [6]. Older drivers also have different preferences on the NDRTs. Clark et al. compared the younger and older drivers' engagement with pre-designed NDRTs and their vehicle control performances in the takeover scenarios. They concluded that older drivers preferred electronic devices less than younger drivers, and they were more likely to brake harder after the takeover if they were more engaged in NDRTs [1].

Previous driving studies usually treated older drivers as one universal cohort, but younger old drivers and older old drivers have distinct behaviors and performance [11]. Among various classifications of older drivers, this study used the classification of three subgroups: the young-old (65–74 years old), the middle-old (75–84 years old), and the old-old (over 85 years old) [12]. In the current experiment, older drivers above 75 years old were recruited, and they are classified into the middle-old and old-old groups based on the standard above. Much research has demonstrated that older drivers exhibited decreased takeover performance compared to younger cohorts. With middle-old and old-old age drivers as our older driver group participants, we aim to explore the impact of age on driver's takeover performance in conditionally driving automation, especially to discern the age difference between older drivers and other cohorts. The metrics of takeover time, resulting acceleration, and lane deviation were included in our study, representing different aspects of older drivers' takeover performance. Also, the current study aims to figure out how distinct factors influence older drivers differently on the metrics mentioned above, compared to young and middle-aged drivers. Those factors include different road types and drive types. Consequently, we can characterize older drivers' takeover performance, as well as their strengths and weaknesses.

2. Methodology

2.1. Participants

Twenty-four young drivers (18-24 years old), twenty-four middle-aged drivers (35-52 years old) and twenty-four older drivers (over 75 years old) were recruited for the experiment. A summary of the participants' descriptive data is provided in Table 1.

Tab. 1. Descriptive Statistics of Participants

Demographic	Young (n = 24)	Mid-aged (n = 24)	Old (n = 24)
Age			
Minimum-Maximum	18-24	35-52	75 +
Mean (SD)	21.15 (3.35)	42.04 (5.87)	80.4 (6.14)
Gender			
Female	11	11	10
Male	13	13	14

Each drivers' consent was obtained before the experiment. To be qualified for the experiment, each driver should hold a valid Canadian driving license (such as Ontario G2 or G) and a minimum of one year of driving experience. Recruitment primarily targeted the communities of Waterloo and Kitchener. Most of the younger drivers are students from the University of Waterloo and neighboring local colleges. Middle-aged drivers, on the other hand, come across our information through posters and social media advertisements. As for the older drivers, the WRAP (Waterloo Research Aging Participant Pool) provided us with the contact details and age profiles of older individuals signed up for forthcoming university studies. This study has been reviewed and received ethics clearance through the University of Waterloo Research Ethic Committee (REB #42299).

2.2. Experiment design

Eight different driving scenarios were included in this experiment. Four distinct types of roads were designed, including straight highways, curved highways, straight city, and curved city roads (see Figure 1). 'Straight' denotes linear trajectories, while 'curve' signifies roads with curved trajectories within the experimental range. Furthermore, 'highway' and 'city' designate different locations distinguished by varying traffic conditions. In the autonomous control time, the level 3 semi-autonomous vehicle drivers at 90 km/h on a two-lane highway and at 30 km/h on an urban, non-highway road. All scenarios included moderate scripted traffic. On the highway, there were 10 vehicles per kilometer per lane, positioned roughly 100 meters from the ego vehicle. In the urban environment, traffic consisted of 6 vehicles per kilometer per lane, along with 2 pedestrians and 2 cyclists, also approximately 100 meters away from the ego vehicle. The automation system managed both longitudinal and lateral control. Longitudinal control functioned similarly to an Adaptive Cruise Control system, adhering to speed limits, adjusting speed in response to slower leading vehicles, and maintaining the vehicle in the center of the current lane. Two driving types were employed, including Autopilot (AP) only and AP with NDRTs. In the AP only scenarios, participants solely employed AP. In the AP with NDRTs scenarios, participants employed the AP first and executed the NDRTs while the automation was on. Each participant did three types of NDRTs, including the Critical Tracking Task (CTT) [7], the Surrogate Reference Task (SuRT) [13], and the n-back tasks [8]. The CTT was a visual distraction task where drivers were tasked with tracking a moving line, adjusting its position using the up and down keys to align it with a central reference line on the screen. The SuRT is also a visual distraction task where drivers were required to identify a unique circle among a display of identical circles. The n-back is an audio distraction task where drivers need to recall numbers from a sequence spoken by the experimenter, with the level of difficulty determined by the number of steps 'n' backward in the series.



Fig. 1. Driving experiment scenarios (left: highway; right: city).

Figure 2 shows the experiment environment settings. In the current study, we used the Logitech G29 steering wheel and pedal set, which allowed us to adjust the force feedback through the accompanying software. We aimed to keep the feedback within the typical range of a standard commercial vehicle. CARLA, an open source driving simulator software, was used to program the simulated takeover driving scenarios. CARLA has been widely used in numerous previous research studies to simulate a variety of driving scenarios [14, 18, 23]. It allowed us to set the takeover time based on the distance to a specified location and also provide both visual warnings on the screen and audible alerts. Each scenario started from a pre-set spot on a highway or city road and the drivers were asked

to enable the autonomous control system at the beginning of the experiment. The autonomous control system followed the same pre-set trajectory in each scenario until the takeover was conducted.



Fig. 2. Experiment environment Settings

2.3. Experiment procedures

Participants' consents were acquired before the experiment. They were briefed on study objectives and tasks, including how to start and stop the automated driving system, their driver responsibilities during the takeover, and conducting in NDRTs. They were informed that the system could handle driving until issuing a TOR, relieving them of continuous monitoring, but also emphasized the importance of their performance on doing NDRTs. We also instructed the drivers to drive as they normally would and asked them to follow the traffic rules at all times, including lane changing, speed limit, and stop sign.

Following this, they did a practice session familiarizing themselves with simulator controls. In each formal experiment trial, the participants would employ the AP at the beginning. They were required to take over control when prompted by a Takeover Request (TOR), which was triggered during the current study. The TOR occurred a few minutes after the scenario began and was issued 7 seconds before the ego vehicle would collide with a hazard positioned ahead. The TOR was delivered in both visual and auditory formats. Each driver completed eight trials for the current experiment in total. The timeline for a typical experimental trial is demonstrated in Figure 3. After the experiment, participants were compensated and thanked for their involvement. The average time duration of the current experiment was approximately 90 minutes.

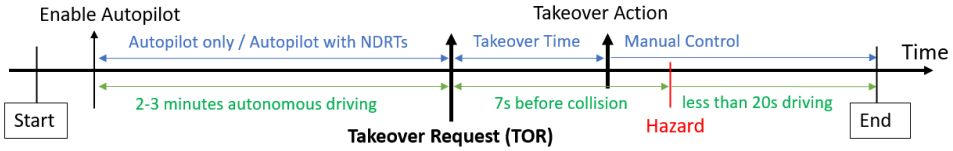


Fig. 3. Timeline for an experimental trial

2.4. Dependent variable

The current study defined drivers' takeover performance from two perspectives: Takeover Time and Takeover Quality.

The takeover time is the period from the TOR given to when the driver conducts a takeover action, including grabbing the steering wheel or stepping on the pedals. It reflects the driver's reaction speed when to the TORs. The Takeover Quality is further represented by Resulting Acceleration and Lane Deviation. Resulting Acceleration refers to the force transferred from the vehicle's tires to the ground. The greater the value is, the more unstable the takeover could be. It is calculated using the equation:

$$Resulting\ Acceleration = \sqrt{MaxLongAcc^2 + MaxLatAcc^2} \qquad (1)$$

In the equation, the maximum longitudinal acceleration (MaxLongAcc) is the maximum force applied during acceleration and braking, and maximum lateral acceleration (MaxLatAcc) is the maximum force that acts transversely to a vehicle's travel direction which occurs during cornering [10]. Lane deviation refers to how much the vehicle crosses a lane marking. The lateral deviation from the center line of the lane was recorded from the start of the takeover until the end of the scenario, and the standard deviation of this lateral deviation was calculated for the values recorded after the takeover. The greater the value is, the less stable the takeover could be. The takeover performance and the takeover quality are obtained from the data saved by the simulator software.

3. Analysis and Results

3.1. Takeover time

Table 2 presents the descriptive statistics of drivers' average Takeover Time and the standard deviation from three age groups under different road types and drive types. In most experimental scenarios, older drivers had longer average Takeover Time compared to younger and middle-aged drivers.

Tab. 2. Descriptive Statistics of Drivers' Average Takeover Time

Road Type	Drive Type	Takeover Time		
		Young	Mid-aged	Old
Highway Straight	AP	2.34 (0.86)	3.45 (3.59)	3.12 (1.41)
	AP with distraction	2.93 (1.24)	3.05 (1.01)	8.20 (7.33)
Highway Curved	AP	2.4 (0.95)	2.86 (1.17)	3.70 (3.06)
	AP with distraction	2.77 (1.09)	2.87 (1.03)	4.07 (2.78)
City Straight	AP	2.64 (0.82)	3.10 (1.16)	4.71 (4.81)
	AP with distraction	2.98 (0.72)	4.30 (2.78)	5.04 (4.36)
City Curved	AP	2.12 (0.89)	2.30 (0.5)	2.18 (0.74)
	AP with distraction	2.50 (0.88)	2.44 (0.6)	4.84 (4.67)

A 3*4*2 three-way mixed-design ANOVA was conducted to analyze the influence of between-subject factor age young, middle-aged, older), and within-subject factors road type (highway straight, highway curved, city straight, city curved) as well as drive type (AP only, AP with NDRTs). Also, the interaction effects between drivers' age and each within-subject factor were explored as well.

Tab. 3. AVOVA on Takeover Time for All Main Effects

	$df_{hypothesis}$	df_{error}	F	p	Effect size (η_p^2)	Observed Power
Age	2	69	17.94	<0.001*	0.342	1.000
Road Type	3	207	6.922	<0.001*	0.091	0.977
Drive Type	1	69	14.385	<0.001*	0.173	0.962

* indicates $p < 0.05$

The results of the main effects on takeover time are listed in Table 3. Different age groups are significantly different on the takeover time. Older drivers had significantly longer takeover time compared to younger and middle-aged drivers (see Figure 4). The post hoc analysis revealed significantly shorter takeover times for young and middle-aged drivers compared to older drivers (both $p < 0.001$), with no significant difference between young and middle-aged drivers ($p = 0.168$). Road type and drive type also show significance as main effects. Figure 5 shows the Estimated Marginal Means (EMMs) of takeover time of different road types and drive types.

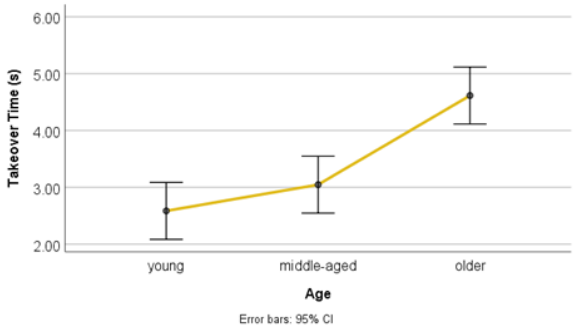


Fig. 4. EMMs of takeover time between different age groups.

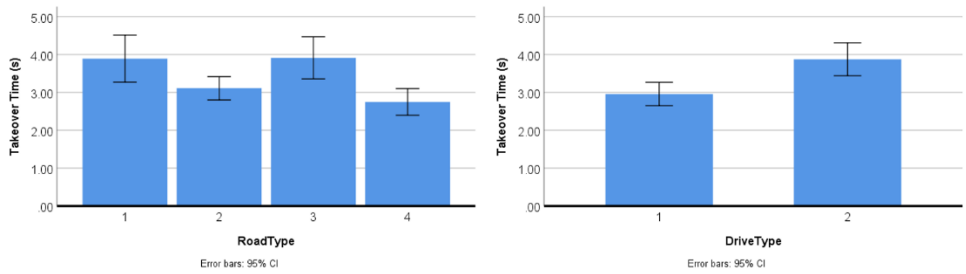


Fig. 5. EMMs of takeover time between different road types (1-highway straight, 2-highway curved, 3-city straight, 4-city curved) and drive types (1-AP only, 2-AP with non-driving-related Tasks).

The interaction between the drive type and age had a significant effect (F (2, 69) = 5.961, p = 0.004, η_p^2 = 0.147, Observation power = 0.866), which indicates that different driving types affect drivers from different age groups differently (see Figure 6). The scenarios with NDRTs were more challenging for older drivers compared to younger drivers, causing significantly higher takeover time for older drivers when driving those scenarios.

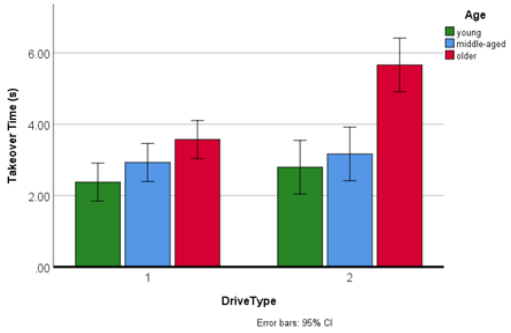


Fig. 6. EMMs of takeover time between different age and drive types (1-AP only, 2-AP with non-driving-related Tasks).

3.2. Takeover quality

3.2.1. Resulting Acceleration

Table 4 presents the descriptive statistics of drivers' average resulting acceleration and the standard deviation from three age groups under different road types and drive types. A 3*4*2 three-way mixed-design ANOVA was conducted to figure out the influence of between-subject factor age, and within-subject factors road type as well as drive type on the resulting acceleration.

The results of the main effects on resulting acceleration are listed in Table 5. There is no significant main effect of age, meaning drivers from all three age groups did not have significant resulting accelerations in the takeover process. However, older drivers did exhibit higher average resulting acceleration values (see Figure 7). Only road type had a significant main effect here (see Figure 8), indicating different road types can result in different resulting accelerations during the takeover. No other interaction effect showed significance.

Tab. 4. Descriptive Statistics of Drivers' Average Resulting Acceleration

Road Type	Drive Type	Resulting Acceleration		
		Young	Mid-aged	Old
Highway Straight	AP	3.90 (1.12)	3.72 (1.05)	3.66 (2.32)
	AP with distraction	3.07 (1.32)	3.59 (1.38)	3.37 (1.42)
Highway Curved	AP	3.81 (1.44)	3.73 (1.34)	6.2 (13.18)
	AP with distraction	3.91 (1.61)	4.35 (1.82)	8.39 (17.95)
City Straight	AP	2.87 (1.01)	2.92 (0.87)	2.95 (0.88)
	AP with distraction	2.99 (1.05)	2.95 (0.97)	2.89 (0.73)
City Curved	AP	3.99 (1.82)	3.7 (0.86)	4.24 (1.61)
	AP with distraction	4.35 (1.46)	3.97 (1.05)	4.43 (1.96)

Tab. 5. AVOVA on Takeover Time for All Main Effects

	$df_{hypothesis}$	df_{error}	F	p	Effect size (η_p^2)	Observed Power
Age	2	69	2.081	0.133	0.57	0.414
Road Type	3	207	4.816	0.003*	0.065	0.900
Drive Type	1	69	0.419	0.520	0.006	0.098

* indicates $p < 0.05$

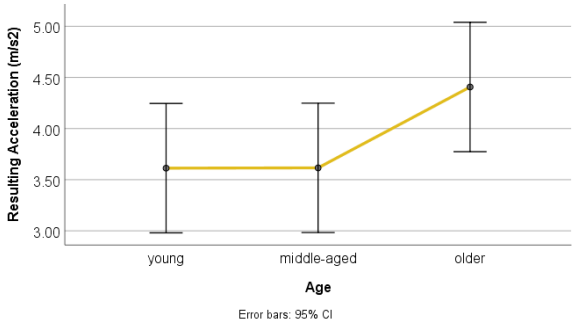


Fig. 7. EMMs of Resulting Acceleration between different age groups

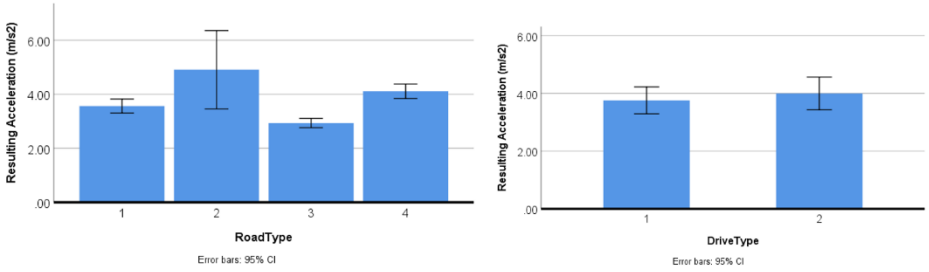


Fig. 8. EMMs of Resulting Acceleration between different road types (1-highway straight, 2-highway curved, 3-city straight, 4-city curved) and drive types (1-AP only, 2-AP with non-driving-related Tasks).

3.2.2. Lane deviation

Table 6 presents the descriptive statistics of drivers' average lane deviation and the standard deviation from three age groups under different road types and drive types. Similarly, a 3*4*2 three-way mixed-design ANOVA was conducted to figure out the influence of between-subject factor age, and within-subject factors road type as well as drive type on the resulting acceleration.

The results of the main effects on lane deviation are listed in Table 7. Different age groups had significantly different lane deviations. Older drivers had significantly larger lane deviation compared to younger and middle-aged drivers (Figure 9). The post hoc analysis revealed significantly shorter takeover times for young and middle-aged drivers compared to older drivers (both $p < 0.001$), with no significant difference between young and middle-aged drivers ($p = 0.168$). Additionally, Road type also shows significance as the main effect (see Figure 10).

Tab. 6. Descriptive Statistics of Drivers' Average Lane Deviation

Road Type	Drive Type	Lane Deviation		
		Young	Mid-aged	Old
Highway Straight	AP	0.66 (0.66)	0.8 (0.57)	0.81 (0.33)
	AP with distraction	0.54 (0.45)	0.62 (0.44)	1.08 (0.8)
Highway Curved	AP	0.86 (0.31)	0.88 (0.2)	0.97 (0.35)
	AP with distraction	0.79 (0.26)	0.78 (0.15)	0.93 (0.44)
City Straight	AP	0.58 (0.36)	0.63 (0.38)	0.77 (0.43)
	AP with distraction	0.57 (0.34)	0.59 (0.36)	0.64 (0.41)
City Curved	AP	0.78 (0.29)	0.83 (0.23)	0.81 (0.22)
	AP with distraction	0.78 (0.27)	0.8 (0.2)	0.74 (0.28)

Tab. 7. AVOVA on Takeover Time for All Main Effects

	$df_{hypothesis}$	df_{error}	F	p	Effect size (η_p^2)	Observed Power
Age	2	69	7.084	0.002*	0.170	0920
Road Type	3	207	9.546	<0.001*	0.122	0.977
Drive Type	1	69	1.674	0.200	0.024	0.248

* indicates $p < 0.05$

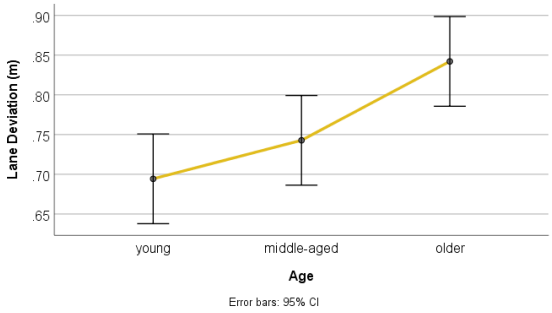


Fig. 9. EMMs of Lane Deviation between different age groups

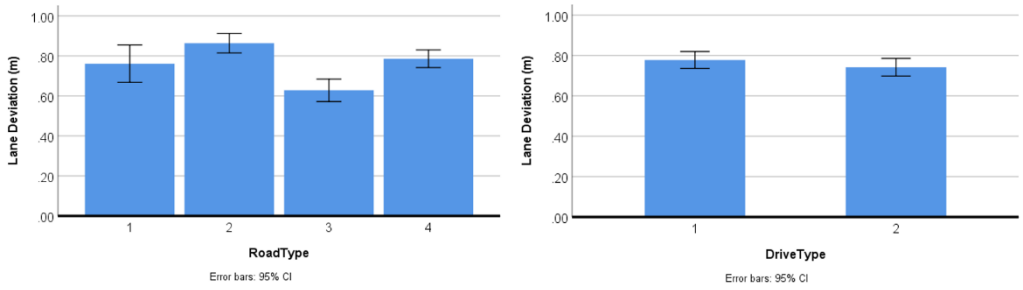


Fig. 10. EMMs of Lane Deviation between different road types (1-highway straight, 2-highway curved, 3-city straight, 4-city curved) and drive types (1-AP only, 2-AP with non-driving-related Tasks)

There was a significant interaction effect between the road type and age (F (6, 207) = 2.578, p = 0.020, η_p^2 = 0.070, Observation power = 0.843), indicating that different road types had different effects on different age drivers. The EMMs of lane deviation between different age and road types can be seen in Figure 11. There are various possible combinations for comparing the four levels of road types. Comparison between road types 1 vs 2, and 3 vs 4 can show the difference between straight and curved roads, while comparison between road types 1 vs 3, and 2 vs 4 can indicate the difference between highway and city roads. However, no significance was detected from the four comparisons above in the tests of within-subject contracts.

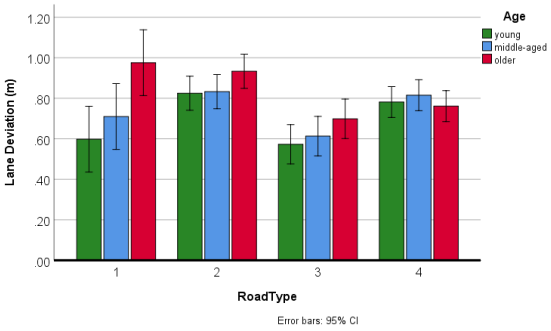


Fig. 11. EMMs of lane deviation between different age and road types (1-highway straight, 2-highway curved, 3-city straight, 4-city curved)

4. Discussion

Takeover time and takeover quality reflect two distinct perspectives of the takeover performance. The takeover time is prone to reflect the speed of reaction after the TOR is issued, while the takeover quality is more relevant to dynamic control of the vehicle. From the results above, the older drivers had significantly longer takeover time compared to young and middle-aged driver groups. This indicates that older drivers need a longer time to complete the takeover process, including perceiving the system-issued requests and taking proper actions to takeover the vehicle manually. If there are hazards in front of the vehicle during the takeover process, older drivers might face a higher chance of crash. Also, the significant interaction effect between age and drive type indicates that NDRTs affect older drivers more compared to the other two driver groups. While these tasks may induce longer takeover times across all driver groups, the impact is notably more pronounced among older drivers. Those findings about takeover times are consistent with previous research. Li et al. found that older drivers had significantly longer takeover time compared to younger drivers in a study using a highly automated vehicle (HAV) [10]. Wu et al. found that NDRTs could delay older drivers' reaction times [24]. Gasne et al. reviewed 14 papers and concluded that level-3 autonomous vehicles brought new challenges for older drivers. Most reviewed articles concluded that older drivers were globally slower at taking over a vehicle than younger drivers [2].

In terms of takeover quality, older drivers had significantly larger lane deviation compared to young and middle-aged drivers. This indicates that older drivers drove less stable after takeover, struggling to maintain the vehicle within the lane's center. Furthermore, the significant interaction effect between age and road type indicates the varying influences of different road types on drivers across age groups. However, further within-subject contracts between different road type levels did not yield meaningful results. While there was no statistically significant difference in the resulting acceleration among the three age groups, older drivers demonstrated a higher average acceleration. In all, older drivers exhibited lower takeover quality compared to the other two driver groups. Diverse conclusions were made about takeover quality from previous research. Favarò et al. concluded that the NDRTs could have a negative effect on lane offset, so drivers' age had no significant effect on that. Körber et al. included lateral acceleration as a dependent variable in their highly automated driving takeover study, and the result also showed no significant difference between the younger and older age group [9].

The older drivers recruited in the current study are categorized as middle-old and old-old age groups, who faced greater impairments of cognitive ability and physical mobility. We believe that the results above provide a more precise depiction of older drivers' takeover performance and facilitate a clearer differentiation between this demographic and others.

5. Conclusions and limitations

This paper attempts to explore the takeover process of older drivers, especially for old-older driver cohort in level-3 autonomous driving condition. Following takeover experiments involving young, middle-aged, and older drivers, multiple ANOVA analysis revealed a significant age-related effect on takeover time and lane deviation. In all, older drivers exhibited longer takeover time and takeover quality compared to other younger drivers. Moreover, they were excessively affected by NDRTs, which distracted their attention during automated driving periods. These findings have direct relevance to the design of TOR. To enhance driving safety, older drivers should be given more time budgets for takeovers in level-3 autonomous driving conditions if possible. Additionally, they should avoid engaging in NDRTs too much to mitigate distractions. Given that level-3 autonomous vehicles offer the advantage of facilitating NDRTs, designers need to be extra careful when integrating such features for older drivers because they require extra time to take over the car when doing a secondary task.

There are several limitations in this study. Firstly, the laptop used for engaging NDRTs should be positioned on the right-hand side of the driver seat during the experiment. This adjustment mirrors the prevalent practice of performing non-driving tasks on the right side of the vehicle, given the placement of driver seats on the left. Secondly, takeover quality could be assessed with a broader range of metrics, thereby enhancing the understanding of age-related impacts on the takeover process. Future studies can attempt to incorporate additional measures to delve deeper into this aspect. Furthermore, we acknowledge that our experimental setup, which uses a low-fidelity simulation, differs from high-fidelity simulators or real vehicles and may influence driver behavior. However, this setup has been commonly used in academic research before and has been validated in previous studies [10, 19], providing reliable insights despite the difference in fidelity. We plan to test the same process in a higher fidelity simulator in the future.

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