

Comparative safety analysis of take-over control mechanisms of conditionally automated vehicles

Original

Comparative safety analysis of take-over control mechanisms of conditionally automated vehicles / Karimi, Arastoo; Barbin, Arash Hassani; Hazoor, Abrar; Marinelli, Giuseppe; Bassani, Marco. - In: ACCIDENT ANALYSIS AND PREVENTION. - ISSN 0001-4575. - ELETTRONICO. - 217:(2025). [10.1016/j.aap.2025.108068]

Availability:

This version is available at: 11583/3006628 since: 2026-01-16T07:50:05Z

Publisher:

Elsevier

Published

DOI:10.1016/j.aap.2025.108068

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright

(Article begins on next page)



Comparative safety analysis of take-over control mechanisms of conditionally automated vehicles[☆]

Arastoo Karimi^{a,*}, Arash Hassani Barbin^a, Abrar Hazoor^b, Giuseppe Marinelli^b, Marco Bassani^a

^a Department of Environment, Land and Infrastructure Engineering, Politecnico di Torino, Torino, Italy, 10129

^b Road Traffic Division, Faculty of Business School, NORDB University, Stjordal, Norway, 7502

ARTICLE INFO

Keywords:

Conditionally automated driving
Take over control
Driver behavior
Critical driving situation
Survival function
Road safety

ABSTRACT

Conditionally Automated driving (CAD) represents a pivotal point in the evolution of automotive technology, bridging full automation and human intervention through effective control mechanisms that ensure safe driver-system transitions. This research consisted of a comparative analysis of take-over mechanisms, focusing on ordinary merging and diverging maneuvers and critical collision-avoidance scenarios. Three take-over control (TOC) methods, including (i) accelerating/braking, (ii) pressing a dedicated button, and (iii) steering, were investigated. Thirty participants were recruited using a mixed factorial design with both within- and between-subject factors. The experimental simulations were conducted on the fixed-base driving simulator. The participants completed three runs on a motorway track comprising ordinary merging and diverging sections, with the final run involving a sudden critical decision to avoid the collision against two crashed vehicles. Weibull accelerated failure time models with and without shared frailty, mixed effects linear regression and multiple linear regression were used to model TOC time, maximum resultant acceleration, and minimum time to collision values.

The results indicate that the pedal mechanism generally provides faster and safer takeovers, especially in critical situations, while the button mechanism results in the longest TOC times, and lowest minimum time to collision values, indicating higher risks. The steering wheel mechanism, associated with the highest maximum resultant acceleration and TOC times in merging and diverging maneuvers, suggests that lateral control may be more cognitively demanding for drivers. These findings emphasize the importance of selecting appropriate TOC mechanisms to improve the safety and efficiency of CAD systems.

1. Introduction

The advent of Conditionally Automated Driving (CAD) systems marks a significant shift in the landscape of vehicle automation, blending advanced technological capabilities with human oversight. These systems are typically classified as Level 3 automation under the Society of Automotive Engineers (SAE) standards (SAE, 2021), and require the driver to take-over control (TOC) when the automated system reaches its operational limits or encounters uncertain conditions. This TOC process is a complex, safety-critical event that requires seamless interaction between the human driver and the vehicle. As the prevalence of CAD vehicles grows, understanding and refining the dynamics of this TOC process becomes crucial. Two principal areas of

investigation in the field of TOC are (i) the length of time required to TOC, and (ii) the quality of the takeover maneuver itself (Weaver and DeLucia, 2020). The take-over time is the period between the system requesting the driver to take control and the driver doing so, and is crucial for safe and effective manual driving. To achieve shorter times, drivers have to respond promptly. Take-over quality deals with how smoothly and safely the driver resumes control, aiming for minimal disruption and continuous safe vehicle operation.

Several factors within the designed system can influence both take-over time and quality. In particular, the time budget plays a crucial role. Research predominantly shows that a short time budget reduces take-over time but also impact negatively on take-over quality (Weaver and DeLucia, 2020). Additionally, take-over request (TOR) signals that

[☆] This article is part of a special issue entitled: 'RSS 2024' published in Accident Analysis and Prevention.

* Corresponding author..

E-mail address: Arastoo.karimi@polito.it (A. Karimi).

are integral to the human–machine interface (HMI) and categorized by Jansen et al. (2022) into visual, auditory, and tactile types, significantly affect the TOC process through their distinct attributes. Previous works indicated that bimodal and trimodal signals prompt quicker driver responses to unexpected driving events than unimodal ones (McNabb, 2017). In addition, the location of TOR equipment such as the instrument cluster, center console, windshield, and head up display play an important role in TOC process (McNabb, 2017; Politis et al., 2017).

Another factor within the system design that can affect TOC is the transition mechanism. This mechanism allows drivers to deactivate the automated system and resume manual control. Various methods for regaining control include pressing a button, rotating the steering wheel, pressing pedals (Zeeb et al., 2016), touching a screen, using voice commands, or employing mid-air gestures (Detjen et al., 2020). The first three methods have been the ones used most in previous works and are widely employed in existing automated vehicles. A number of studies have employed a single method such as a button on the steering wheel (Chen et al., 2021; Huang and Pitts, 2022; Tan and Zhang, 2022; Yoon et al., 2021) or pedals (Melcher et al., 2015), with some studies presenting multiple methods (Du et al., 2020; Wu et al., 2022; Wu et al., 2021). Louw et al. (2015) found that drivers predominantly used the brake in both critical (i.e., an impending collision scenario) and non-critical (i.e., ordinary lane-change of a front vehicle) events in heavy fog, while turning the steering wheel was the second most utilized method when all options were available. In contrast, only a few drivers used the button. However, in non-critical events in light fog, the order of method used was (i) turning the steering wheel, (ii) pressing the button, and then (iii) braking. Gold et al. (2013) observed that increasing the time budget led to a rise in steering inputs relative to braking when overriding automation.

The duration time for lane-change maneuvers tends to be longer and significantly more variable for drivers who use braking to TOC compared to those who used the steering wheel (Petermeijer et al., 2017). Additionally, the steering wheel angle is greater during lane changes, suggesting a lower quality of control with braking relative to steering as a takeover mechanism. The results from Petermeijer et al. (2017) were almost similar across the modalities of auditory, vibrotactile, and their combination. When examining both critical (a damaged stationary car in a lane not occupied by the ego vehicle) and non-critical situations (a stationary damaged vehicle in front of the ego lane) when both the steering wheel and braking pedals are available for overriding automation, Wu et al. (2019) observed that the reaction times of drivers who preferred steering is slower than those who chose braking. This implies that tasks involving lateral control could necessitate greater cognitive effort and longer decision-making times, potentially leading to longer TOC times. These results align with those of Zeeb et al. (2017), who concluded that the effects of a cognitive task load on driver intervention types varies: reaction times and takeover quality deteriorates with increased cognitive load during steering maneuvers, though these effects are not significant for braking interventions. Wu et al. (2022) also found braking reaction times to be shorter than steering reaction times and regarded the minimum of these two as the TOC time for each driver.

Despite existing insights, a comprehensive investigation into the specific effects of different TOC mechanisms has yet to be undertaken. Although some studies consistently use only one mechanism in their experiments (Chen et al., 2021; Huang and Pitts, 2022; Tan and Zhang, 2022; Yoon et al., 2021), such as a button on the steering wheel or the pedals, no comparisons between them have been made. Additionally, some studies introduce multiple TOC mechanisms simultaneously within the same experiment (Du et al., 2020; Wu et al., 2022; Wu et al., 2021), which makes it difficult to compare their individual effects. This complicates the analysis and limits the ability to determine the effectiveness of each mechanism under specific conditions. Such approaches restrict the ability to generalize findings across different TOC mechanisms, a limitation highlighted by Merlhiot and Bueno (2022) in their

systematic review. This gap underscores the need for our research to systematically evaluate and compare the impacts of various TOC mechanisms on takeover time and quality, thereby advancing the understanding of human–automation interaction in CAD systems.

This research presents an experimental comparison of various TOC mechanisms, including accelerating/braking, pressing a button, and steering, conducted through dedicated test drives on a driving simulator. The purpose of the work is to analytically isolate and compare the individual effects of each different TOC mechanism on driving performances. Furthermore, two additional research layers are added by addressing both merging and diverging maneuvers as well as inserting a critical situation designed to generate a potential collision. Therefore, the core research question of this thesis is as follows: how do different TOC methods affect driving performance in merging/diverging maneuvers and safety in critical situations?

2. Methods

2.1. Driving simulator

The driving simulation experiments were conducted at the TRAFIKLAB in NORD University, Norway. The laboratory was equipped with a fixed-base driving simulator provided by AV Simulation (France) operating with SCANER Studio® software. The simulator features three 43-inch screen monitors (1920 x 1080 pixels) and providing a total field of view of 140° horizontally and 30° vertically. The simulator also included force–feedback steering wheels, pedals, manual gearboxes, and adjustable seat. Additionally, vibration pads were integrated to simulate pavement roughness, wheel rolling, and shocks. The simulator was equipped with a 2.1 surround sound system, which reproduced realistic sounds of car engines, roads, wind, and other environmental noises, thereby enhancing the immersive experience.

2.2. Implemented CAD and HMI characteristics

The CAD system was simulated in the experiment. Once automation was activated by the driver using a button on the steering wheel, the system managed the driving operation until it reached predefined points that simulated uncertain conditions or operational limits. At these points, the system used the HMI to prompt the driver to resume control of the vehicle and perform whatever maneuvers were necessary. Three pieces of information were provided to the driver via visual messages on the HMI: (i) the current driving mode, indicating whether automated driving was active or not (Fig. 1a and 1b, respectively), (ii) autonomous mode available, together with a beep sound, prompting the driver to activate automated driving (Fig. 1c), and (iii) resume control or TOR, accompanied by an auditory alert (Fig. 1d). A 5 s time budget was selected (Doubek et al., 2020; Mok et al., 2015), a duration sufficient for drivers to TOC while still presenting a challenge, particularly in critical situations. This time frame was chosen because it was shown to result in a few collisions, making it effective for testing driver responses (Doubek et al., 2020; Mok et al., 2015).

2.3. Test track

The test track was a two-lane freeway with a speed limit of 110 km/h, connected to another similar two-lane freeway via a ramp. This ramp included a series of curves designed for a speed limit of 70 km/h, including simple curves with a length of 150 m and a radius of 200 m. These simple curves were connected to the straight sections by spiral curves with a length of 40 m. Fig. 2 shows a scheme of the test track designed according to AASHTO (2018) standards. The lane and shoulder width were 3.6 and 3.0 m, respectively. The diverging ramp terminal included a taper segment of 75 m and a deceleration lane with a length of 120 m and a width of 3.6 m. The merging ramp terminal had an acceleration lane with a length of 200 m and a width of 3.6 m; the taper

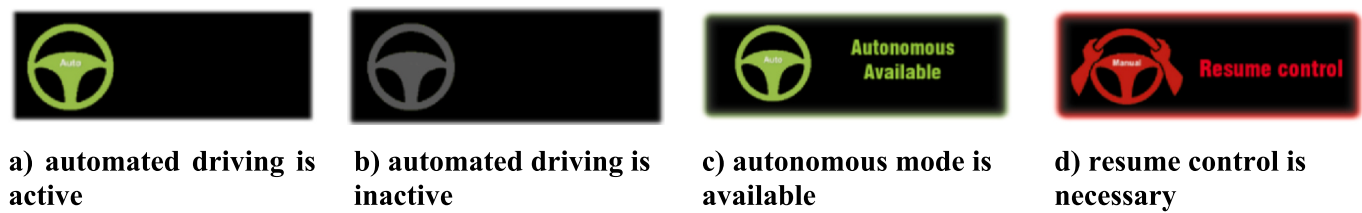


Fig. 1. Vehicle HMI.

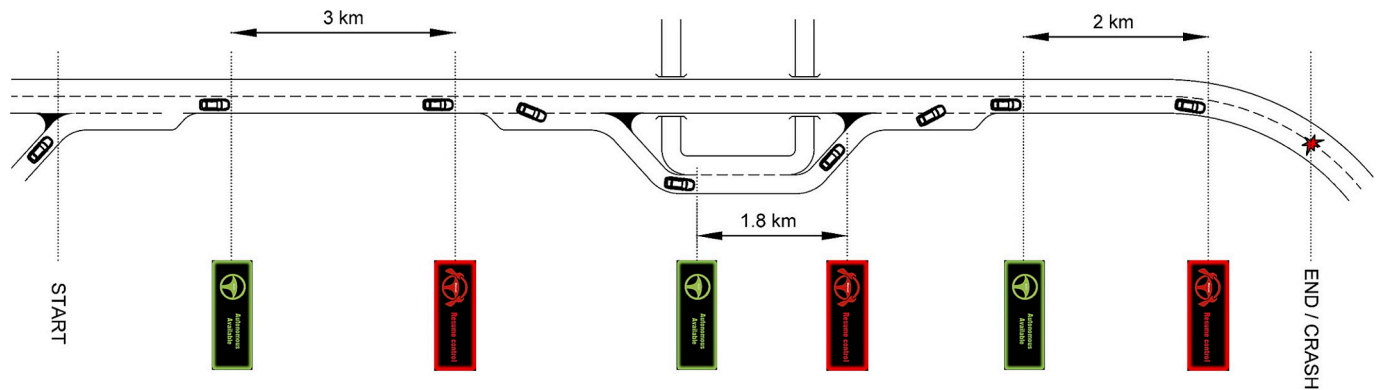


Fig. 2. Scheme of the test track and driving simulation scenario.

length of the merging terminal was 90 m.

2.4. Experimental design

This study conducted a detailed comparative analysis of take-over mechanisms in ordinary (non-critical) merging and diverging maneuvers, and critical situations where the driver had to suddenly regain control of the vehicle when two crashed vehicles were visible on the rightmost lane of a curve with an available sight distance limited to 150 m. This distance was selected to generate a TOR equal to 5 s before the crash site. The same TOR was issued 5 s before the start of the taper for diverging and merging the motorway. A within-subject design was employed for such non-critical merging and diverging maneuvers, allowing each participant to drive three times on the test track, with a different take-over mechanism active during each run dispensed in a randomized order: (i) accelerating/braking, (ii) pressing a dedicated button, and (iii) steering. Although some vehicles were present to make the environment realistic, they did not affect the subject vehicle's maneuvers in this study.

To minimize bias that might arise from repeated exposure, a between-subject design was implemented for the critical situation. Therefore, each participant was exposed to the critical situation only once, with this occurring on the last run and involving randomly assigned take-over mechanism. Assuming a separate analysis for merging and diverging situations, a factorial multilevel categorical design was used, with drivers treated as a block and a significance level of 0.05. The power of this design was 99.9 % with 30 participants, indicating a very low probability of Type II errors. The assignment of the critical situation to a specific take-over mechanism ensured that each mechanism was tested by one-third of the participants, yielding a power of 97.3 % for this portion of the study.

The remaining non-critical test runs employed the other take-over mechanisms in a random sequence for each participant. Fig. 2 illustrates the scheme of the final run for each participant; the first two runs did not include the critical event.

2.5. Participants

In accordance with the Code of Ethics of the Association (2024), thirty Norwegian licensed drivers participated in the experiment on a voluntary basis without receiving any benefit or payment. The participants included 15 males and 15 females aged between 23 and 38 ($M = 28.5$ years; $SD = 5.0$ years). The participants had an average of 8.5 years of driving experience ($SD = 4.3$ years) and reported an annual driving distance of 16654 km per year ($SD = 7339$ km per year). On average, participants had been involved in 0.73 crashes ($SD = 0.82$). An equal representation of male and female participants was selected to reduce potential gender bias. Participants were chosen from the young to middle-aged demographic, as this group is more likely to adopt and utilize the latest automotive technologies, including CAD (Classen et al., 2024). Prior to the data collection, the Norwegian Agency for Shared Services in Education and Research (SIKT) was informed about the study and approved the planned procedures to follow the ethical guidelines and to respect the privacy of participants (ref. nr. 909586).

2.6. Experiment protocol, data collection, and manipulation

The simulator experimental protocol ensured that participants (i) completed a pre-drive questionnaire, (ii) received an overview of the system's functionality and operation, (iii) drove the three simulated scenarios with three-minute rest intervals, all preceded by a pre-drive training session which was repeated before each driving session, (iv) completed a survey between each session, and (v) completed a post-drive questionnaire.

The pre-drive questionnaire was designed to gather participants' demographic information. It is worth pointing out that a pre-drive questionnaire was provided online along with the invitation letter during the recruitment phase. At the driving simulator laboratory, drivers received an overview of the system's functionality and the meaning of HMI messages. During the pre-drive training sessions, participants received an explanation and tested the available transition method for the upcoming driving session several times on a straight road track to get familiar with the method. After each driving session, participants completed surveys rating the take-over mechanism on an acceptance

scale (Van Der Laan et al., 1997) for merging/diverging maneuvers and critical situations. At the end of the experiment, participants completed the post-drive questionnaire to indicate their preference among the three different take-over mechanisms (i.e., accelerating/braking, pressing a dedicated button, and steering). Additionally, drivers provided feedback by filling out a simulator sickness questionnaire and none reported experiencing it. Participants were also asked to report their prior experience with conditionally automated driving (CAD) and advanced driver assistance systems (ADAS). As shown in Table 1, half of the participants indicated prior experience with CAD, and the majority had previously used specific ADAS features, such as Adaptive Cruise Control (ACC), Intelligent Speed Adaptation (ISA), Autonomous Emergency Braking (AEB), and Lane Keeping Assist/Warning (LKA). To minimize the potential influence of familiarity with the CAD, a training session was included in the protocol before each experimental drive. Before starting each run, the driver was informed that ‘Oslo’ was their destination. The destination was communicated to the driver by means of traffic signs. The automated vehicle operated in the right lane at a speed of 110 km/h. Participants were instructed to keep their hands off the steering wheel and their feet off the pedals while using the automated mode. They were not allowed to deactivate or activate the automated system on their own but only when they received the TOR.

As indicated in Fig. 3, the exact times of the vehicle’s take-over request and the driver’s take-over control were recorded to calculate the corresponding TOR and TOC times, respectively. Additionally, the speed, the longitudinal and lateral position, and the longitudinal and lateral acceleration of the subject (ego) vehicle for 5 s after take-over were extracted at a frequency of 100 Hz. From this raw data, the maximum resultant acceleration and deceleration observed within a 5 s period post-take-over were employed as metrics to evaluate take-over quality for both diverging and merging maneuvers.

2.7. Statistical analysis

2.7.1. Modelling take-over control time

Time duration models are pivotal in analyzing time-to-event (survival) data, as they precisely delineate the influence of various factors on the timing of events (Kleinbaum et al., 2012). This detailed understanding enables accurate predictions, which are crucial for this study’s focus on modelling take-over times and evaluating different factors, including TOC mechanisms.

T is a nonnegative and continuous random variable representing take-over time, characterized by a probability density function $f(t)$ and a cumulative distribution function $F(t)$. The survivor function $S(t)$, which is the probability that a driver fails to take-over control in time t is defined as Eq. (1). The hazard function $h(t)$ is defined in Eq. (2), and represents the rate at which a driver is likely to TOC immediately after time t , given that the take-over has not occurred up until t . This function measures the intensity of the risk of the event occurring at each moment, rather than providing a direct probability of the event:

$$S(t) = Pr(T \geq t) = 1 - F(t) \tag{1}$$

Table 1

Participants with experience in CAD and ADAS modules (No. of participants = 30).

| Usage | CAD | ACC | ISA | AEB | LKA |
|-----------|-----|-----|-----|-----|-----|
| Never | 15 | 1 | 5 | 11 | 4 |
| Seldom | 7 | 4 | 12 | 8 | 9 |
| Sometimes | 4 | 7 | 4 | 2 | 5 |
| Often | 2 | 13 | 7 | 6 | 9 |
| Always | 2 | 5 | 2 | 3 | 3 |

Note: CAD = Conditionally Automated Driving; ACC = Adaptive Cruise Control; ISA = Intelligent Speed Adaptation; AEB = Autonomous Emergency Braking; LKA = Lane Keep Assist/Warning.

$$h(t) = \lim_{\Delta t \rightarrow \infty} \frac{Pr(t < T \leq t + \Delta t | T \geq t)}{\Delta t} = \frac{f(t)}{1 - F(t)} \tag{2}$$

The Accelerated Failure Time (AFT) and proportional hazard parametric models are two distinct approaches for assessing the impact of covariates on a hazard function. The AFT model captures the direct effect of a factor on survival time. This approach allows for a simpler interpretation of results, as the estimated parameters directly quantify the effect of each covariate on the mean TOC time (Haque and Washington, 2014). Consequently, the AFT model was employed in this study. The AFT model is defined by Eq. (3) in which the natural logarithm of take-over time is a linear function of independent variables:

$$\ln(T) = \beta X + \varepsilon \tag{3}$$

where X and β are the vectors of independent variables and estimable parameter, respectively, and ε is the error term. The take-over time exhibits positive duration dependence, with the likelihood of a driver taking over control increases over time. These events, characterized by a monotonically increasing hazard rate, are well-modelled by the Weibull distribution when its shape parameter p is greater than 1, indicating that the probability of a take-over increases with time. Therefore, the Weibull model is appropriately applied to analyze take-over time in this study. The hazard and survival functions of the Weibull duration model are defined by Eq. (4) and Eq. (5), respectively:

$$h(t) = p t^{p-1} \exp(-p\beta X) \tag{4}$$

$$S(t) = \exp(-t^p \exp(-p\beta X)) \tag{5}$$

The hazard rate increases with take-over time when $p > 1$ and decreases when $p < 1$. Notably, the Weibull distribution simplifies to an exponential distribution when $p = 1$.

Given that this experiment adopted a within-subject design for non-critical take-over controls, unobserved heterogeneity poses a significant challenge. Incorporating shared frailty, akin to random effects models, effectively addresses this unobserved heterogeneity. The Weibull AFT with shared frailty can be expressed by Eq. (6) and Eq. (7):

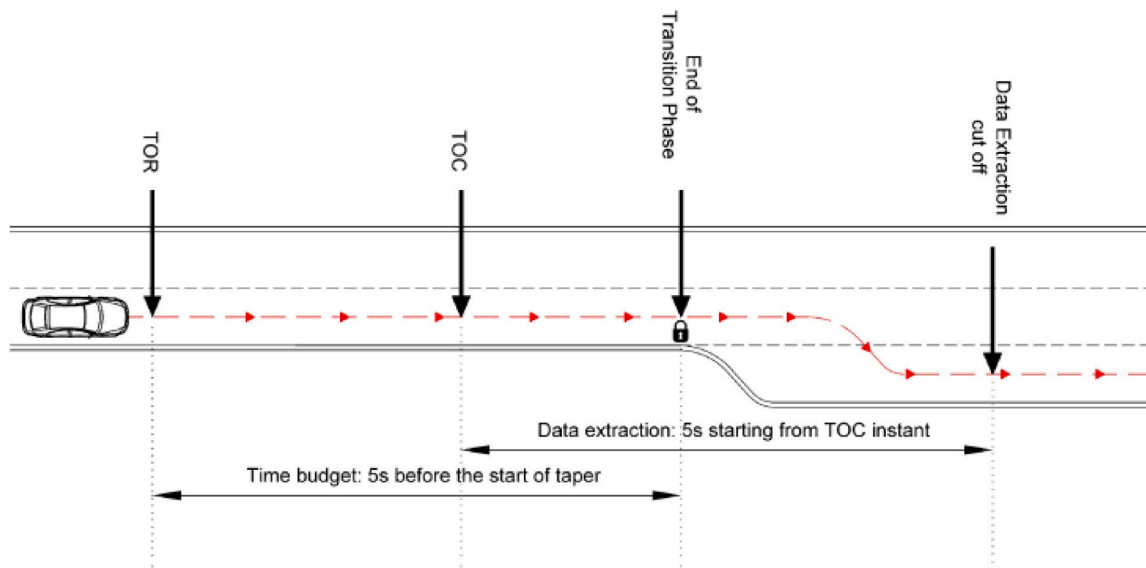
$$h_{ij}(t|\alpha_i) = \alpha_i h_{ij}(t) \tag{6}$$

$$S_{ij}(t|\alpha_i) = \exp\left(-\int_0^t h_{ij}(u|\alpha_i) du\right) = \exp\left(-\alpha_i \int_0^t h_{ij}(u) du\right) \tag{7}$$

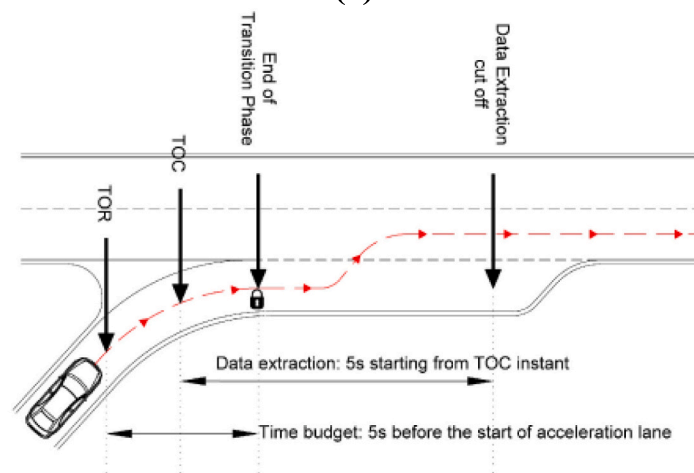
where h_{ij} and S_{ij} are the hazard and survival functions, respectively, for the i^{th} driver using the j^{th} observation; α_i represents the frailty of i^{th} driver and is assumed to follow a Gamma distribution with a mean of one and a variance of θ . Parameters of model were estimated using maximum likelihood method.

2.7.2. Modelling take-over control quality and safety

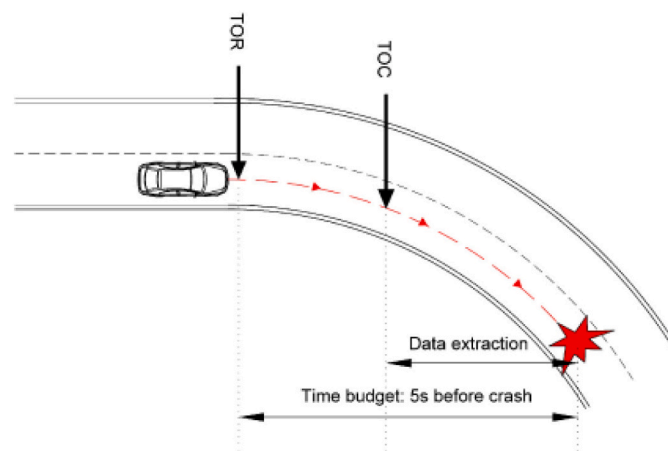
For non-critical conditions, Maximum Resultant Deceleration (MRD) and Maximum Resultant Acceleration (MRA) values within 5 s after the driver had resumed control were determined as a TOC quality measurement for diverging and merging maneuvers, respectively. The term ‘resultant’ refers to the magnitude of the vector combining both longitudinal (along the direction of travel) and lateral (perpendicular to the direction of travel) components of vehicle acceleration or deceleration. This parameter was chosen because it covers a broad spectrum of vehicle dynamics (Tanshi and Soffker, 2022). The Mixed-effect linear model was used to model MRD and MRA since there were repeated measurements for participants and since both are continuous. For critical situations, Minimum Time-to-Collision (MTTC) was used. Time-to-Collision (TTC) was calculated by dividing the remaining distance to the crashed vehicles by the vehicle’s speed when the vehicle was in the right lane of the road. The smallest TTC value measured since the ego vehicle was in the rightmost lane was considered as MTTC, and multiple linear regression was used to model the MTTC. The details of both mixed-effects linear



(a)



(b)



(c)

Fig. 3. Scheme of Automation Control and Data Extraction in non-critical (a) diverging and (b) merging manoeuvres, and (c) critical situation (figure not in scale).

and multiple linear regression models can be found in Wooldridge (2018). The Mixed-effect linear model was also used to analyze participants' self-evaluation of the TOC mechanisms, including their perceived usefulness and satisfaction.

3. Results

3.1. Results on driving performance

Table 2 presents a summary of dependent variables. In five instances during diverging scenarios, the driver took control of the vehicle before the TOR, resulting in five missed data points from the planned 90 observations. Consequently, a total of 205 observations were collected: 85 for diverging maneuvers, 90 for merging, and 30 for critical situations. On five occasions during diverging scenarios, the driver took control of the vehicle before the TOR, resulting in five missed data points out of the planned 90 observations. The descriptive statistics indicate that the longest average TOC time was associated with the steering wheel mechanism in both diverging and merging conditions, except in critical situations, where the button mechanism had the longest average TOC time. The shortest average TOC time was associated with the pedal mechanism in all conditions except diverging. The steering wheel mechanism resulted in the highest average MRD and MRA with the most severe variation in diverging and merging conditions, respectively, within 5 s after taking over control. In the diverging condition, all participants resumed control within the time budget (i.e., 5 s). However, in the merging condition, two participants slightly exceeded this time when the steering wheel was the active mechanism. In critical situations, all participants reacted within the time budget except one who was using the button mechanism. Nevertheless, four collisions did occur: three with the button mechanism and one with the steering wheel one. For these collisions, the MTTC value is zero (Table 2). Table 2 shows that the longest average MTTC, indicating the safest situation, was observed when the pedal mechanism was active. The worst situation was associated with the button mechanism, which had the shortest average MTTC.

Table 3 presents the estimated TOC time models for three different

Table 2
Descriptive Statistics of Dependent Variables Based on Take-over Mechanisms and Conditions. (Noted: M = mean, SD = standard deviation).

| Variables | TOC mechanisms | Unit | M | SD | Min. | Max. |
|--------------------------------------|----------------|------------------|------|------|------|------|
| Diverging | | | | | | |
| Take-over (TOC) time | Button | s | 1.55 | 0.57 | 0.65 | 2.69 |
| | Pedals | s | 1.61 | 0.82 | 0.63 | 3.93 |
| | Steering wheel | s | 2.66 | 1.03 | 0.04 | 4.29 |
| Maximum Resultant Deceleration (MRD) | Button | m/s ² | 1.05 | 0.48 | 0.63 | 2.53 |
| | Pedals | m/s ² | 0.95 | 0.39 | 0.48 | 2.37 |
| | Steering wheel | m/s ² | 1.41 | 0.56 | 0.74 | 2.96 |
| Merging | | | | | | |
| Take-over (TOC) time | Button | s | 1.69 | 0.48 | 0.94 | 2.94 |
| | Pedals | s | 1.40 | 0.39 | 0.59 | 1.89 |
| | Steering wheel | s | 2.38 | 1.02 | 1.29 | 5.19 |
| Maximum Resultant Acceleration (MRA) | Button | m/s ² | 2.15 | 0.19 | 1.89 | 2.58 |
| | Pedals | m/s ² | 2.22 | 0.18 | 1.97 | 2.67 |
| | Steering wheel | m/s ² | 2.24 | 0.29 | 1.80 | 3.02 |
| Critical situation | | | | | | |
| Take-over (TOC) time | Button | s | 2.49 | 1.55 | 1.39 | 6.64 |
| | Pedals | s | 1.04 | 0.33 | 0.49 | 1.74 |
| | Steering wheel | s | 2.00 | 1.19 | 1.19 | 2.69 |
| Minimum Time-to-Collision (MTTC) | Button | s | 1.35 | 1.15 | 0.00 | 3.03 |
| | Pedals | s | 3.07 | 0.72 | 1.33 | 3.85 |
| | Steering wheel | s | 1.81 | 0.84 | 0.00 | 3.09 |

conditions: diverging maneuvers, merging maneuvers, and critical situations. Using the STATA statistical software (StataCorp, 2017), Weibull AFT models with shared frailty were applied to the data from non-critical situations, which include diverging and merging maneuvers. However, since the critical situation does not involve repeated measures, a Weibull AFT model without shared frailty was estimated. The results of the likelihood ratio (LR) tests demonstrate that all three models are significant in overall terms ($\chi^2 > 20$, p -value < 0.0001). Table 3 indicates that the shape parameter, p , of the Weibull distribution for all models is greater than 1, suggesting that the probability of a takeover increases as the duration extends. The results of the LR test showed that the θ values were statistically significant ($\chi^2 > 6$, p -value < 0.01) for both Weibull AFT models with shared frailty in the diverging and merging conditions, implying that the shared frailty was significant.

The results indicate that TOC mechanisms significantly affect TOC time at the 95 % confidence level. As shown in Table 3, significant differences were observed in TOC times when using the steering wheel and pedals compared to the button. However, in the diverging condition, the difference in TOC time between the pedals and button mechanisms was not significant at the 95 % confidence level. No statistically significant effects related to the age and gender of participants were found at the 95 % confidence level. The positive and negative coefficients associated with the pedal and steering wheel mechanisms, respectively, suggest that using these mechanisms instead of the button (baseline mechanism) leads to a deceleration and acceleration of the TOC time. For example, in the merging condition, the TOC time when using the pedal mechanism should be multiplied by $e^{-0.162} = 0.85$ s compared to the baseline mechanism. This indicates that the TOC time is 15 % shorter with the pedal mechanism than when using the button. Since the average TOC time for the button mechanism is $e^{0.495} = 1.64$ s, this means that drivers will regain control 0.25 s sooner with the pedal mechanism than with the steering wheel one.

Table 4 shows the estimation of linear mixed model parameters of MRD for diverging and MRA for merging maneuvers. The results of the LR test demonstrated that the inclusion of random effects significantly improved the model fit at the 95 % confidence level. The overall significance of models was tested by LR tests which implied that models for diverging and merging conditions were significant at 95 % and 90 % confidence levels, respectively. The model's results suggested that there was a significant difference in MRD and MRA when comparing the steering wheel to the button TOC mechanism at the 95 % confidence level. However, no significant differences were observed between the pedal and button TOC mechanisms.

The results of the linear regression model presented in Table 4 indicated that the model was significant at the 95 % confidence level and since the TOC mechanism was the only factor included, this made it responsible for about 37 % of all the variability in the MTTC values. Using pedals as the TOC mechanism resulted in higher MTTC values compared to using a button, signifying a safer situation.

3.2. Results from self-evaluation

At the conclusion of each driving session, participants evaluated the TOC mechanisms using the System Acceptance Questionnaire (Van Der Laan et al., 1997), which consists of nine scales subsequently grouped into two subscales: usefulness and satisfaction. The subscales of usefulness and satisfaction represent participants' evaluations of the TOC mechanisms' effectiveness and their overall comfort, respectively. Fig. 4a illustrates the distribution of ratings for the three TOC mechanisms on a scale ranging from + 2 (maximum positive rating) to -2 (maximum negative rating) during merging and diverging maneuvers. Linear mixed models were employed to assess statistically significant differences among the three TOC mechanisms, with Scheffé's method applied for post-hoc adjustments to evaluate usefulness and satisfaction. The results revealed significant differences ($p < 0.001$) across all paired comparisons. The pedal mechanism received the highest ratings,

Table 3
Estimation of the Weibull AFT Models with Shared Frailty for TOC Time.

| | Diverging | | | Merging | | | Critical | | |
|----------------|-----------|-----------|-----------------|---------|-----------|-----------------|----------|-----------|-----------------|
| | β | Std. err. | <i>p</i> -value | β | Std. err. | <i>p</i> -value | β | Std. err. | <i>p</i> -value |
| TOC mechanism | | | | | | | | | |
| Pedals | 0.048 | 0.0977 | 0.623 | - 0.162 | 0.0619 | 0.009 | -1.055 | 0.1738 | 0.000 |
| Steering wheel | 0.565 | 0.0941 | 0.000 | 0.346 | 0.0663 | 0.000 | -0.426 | 0.1750 | 0.015 |
| Constant | 0.458 | 0.079 | 0.000 | 0.495 | 0.0590 | 0.000 | 1.164 | 0.1311 | 0.000 |
| <i>p</i> | 2.981 | 0.3722 | - | 4.552 | 0.5048 | - | 2.643 | 0.3537 | - |
| θ | 0.310 | 0.1865 | - | 0.716 | 0.2888 | - | - | - | - |
| # observations | 85 | - | - | 90 | - | - | 30 | - | - |

Table 4
Estimation of Linear Mixed-Effect Models of MRD and MRA (Diverging and Merging Conditions) and Linear Regression Model of MTTC (Critical Condition).

| | Diverging | | | Merging | | | Critical | | |
|---------------------------|-----------|-----------|-----------------|---------|-----------|-----------------|----------|-----------|-----------------|
| | β | Std. err. | <i>p</i> -value | β | Std. err. | <i>p</i> -value | β | Std. err. | <i>p</i> -value |
| TOC mechanism | | | | | | | | | |
| Pedals | - 0.100 | 0.1140 | 0.379 | 0.071 | 0.0449 | 0.114 | 1.723 | 0.4115 | 0.000 |
| Steering wheel | 0.351 | 0.1128 | 0.002 | 0.093 | 0.0449 | 0.039 | 0.457 | 0.4115 | 0.277 |
| Constant | 1.055 | 0.079 | 0.000 | 2.148 | 0.0407 | 0.000 | 1.350 | 0.2910 | 0.000 |
| Random-effects parameters | | | | | | | | | |
| σ^2 of intercepts | 0.046 | 0.030 | - | 0.020 | 0.0078 | - | - | - | - |
| σ^2 of residuals | 0.181 | 0.034 | - | 0.030 | 0.0055 | - | - | - | - |
| # observations | 85 | - | - | 90 | - | - | 30 | - | - |

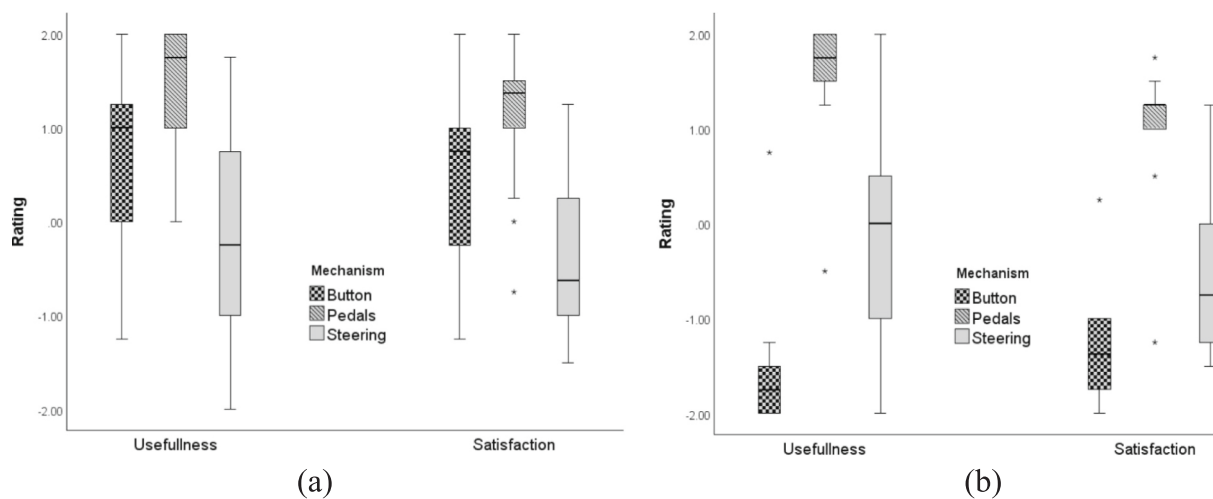


Fig. 4. System Acceptance rating for TOC mechanisms based on usefulness and satisfaction scale in (a) diverging and merging maneuvers (b) crash situation/critical condition.

followed by the button mechanism, with the steering mechanism receiving the lowest ratings.

At the conclusion of the final driving session, participants also evaluated the three TOC mechanisms specifically for the critical condition (crash scenario). Fig. 4b presents box plots comparing the ratings of the mechanisms on usefulness and satisfaction scales. Statistically significant differences were observed for all paired comparisons among the mechanisms ($p < 0.05$), except for the satisfaction scale comparison between the steering wheel and the button. The pedal mechanism consistently received the highest ratings on both scales, with a higher median and lower variability compared to the other mechanisms. This indicates that participants perceived it as the most effective and satisfying option in critical situations. The steering mechanism demonstrated moderate performance, with ratings clustered closer to neutral and greater variability, reflecting mixed participant opinions. In contrast, the button mechanism was rated the lowest across both subscales, with negative median ratings, although its satisfaction scale rating was not significantly different from that of the steering wheel. These results suggest that participants found the steering mechanism to be the least

effective and, along with the button, least satisfactory option for managing a critical condition.

At the end of the experimental session, participants were asked to provide their preferences about the three TOC mechanisms. Specifically, participants responded to two questions in a multiple-choice option: (i) which TOC mechanism did you prefer during the simulator experiments? and (ii) if you had to choose, which TOC mechanisms would you want in your vehicle?

In response to the first question, the majority of participants (26 out of 30) selected the pedal mechanism as their preferred TOC option, while three participants preferred the button mechanism and only one participant chose the steering mechanism (Fig. 5a). Similar results were observed for the second question. In this case, all participants selected the pedal mechanism except for one. Additionally, since participants were allowed to choose multiple options, some expressed a preference for combinations of two or three mechanisms, as illustrated in Fig. 5b. These results demonstrate the strong preference for the pedal mechanism across both questions, reflecting its perceived ease of use and effectiveness. The allowance for multiple selections in the second

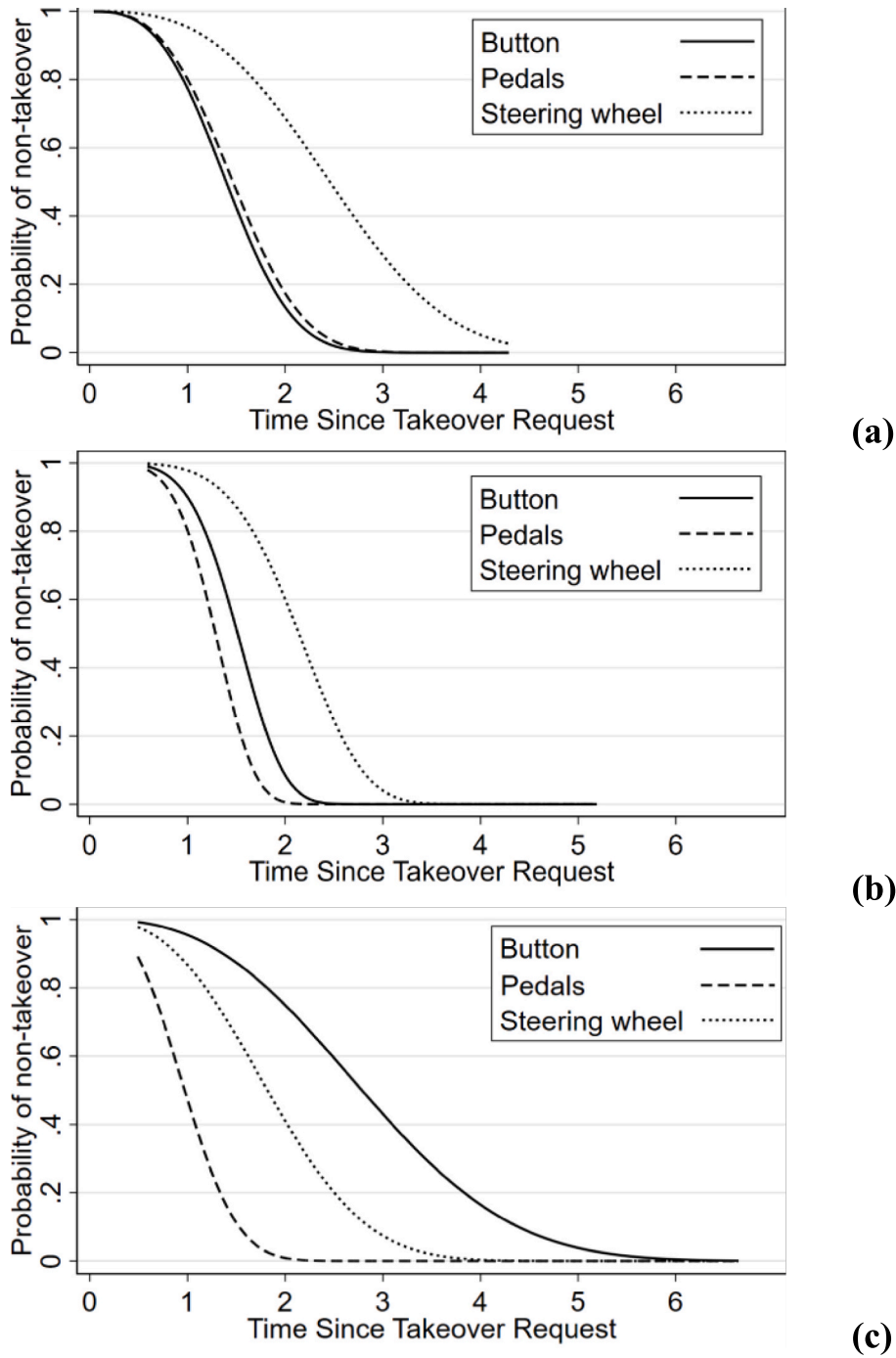


Fig. 6. Survival curves for TOC time in 3 different conditions: (a) diverging, (b) merging, and (c) critical situation.

quicker and safer takeovers, especially in critical situations. In contrast, the button mechanism resulted in the longest TOC times and the lowest MTTC values, indicating higher risks in critical situations. The steering wheel mechanism resulted in the highest MRD, MRA, and TOC times in non-critical situations, suggesting that lateral control might be more cognitively demanding for drivers. These insights underscore the importance of selecting appropriate TOC mechanisms to enhance the safety and efficiency of CAD systems and ensure better preparedness and responses from drivers when manual intervention is required. The results of this study can be used to improve the transferability of previous works that used only one mechanism, such as a button. This is particularly relevant when combining the results of previous studies, which may suffer from the limitation of not considering the effect(s) of specific

TOC mechanisms.

Future research should continue to explore the dynamics of the human-automation interaction process and consider the integration of multi-modal TOC mechanisms to optimize driver responses in varying scenarios. A limitation of this study was the absence of non-driving-related tasks, which are probable in CAD vehicles and should be included in future research. In this study, traffic variables were not considered as factors affecting the subject vehicle's merging, diverging, or collision-avoidance maneuvers. Future research could examine how the behavior of surrounding traffic influences driver decision-making and response effectiveness in both ordinary and critical take-over scenarios. Additionally, the interaction of different traffic- and geometric-related variables, as well as various time budgets, with various TOC

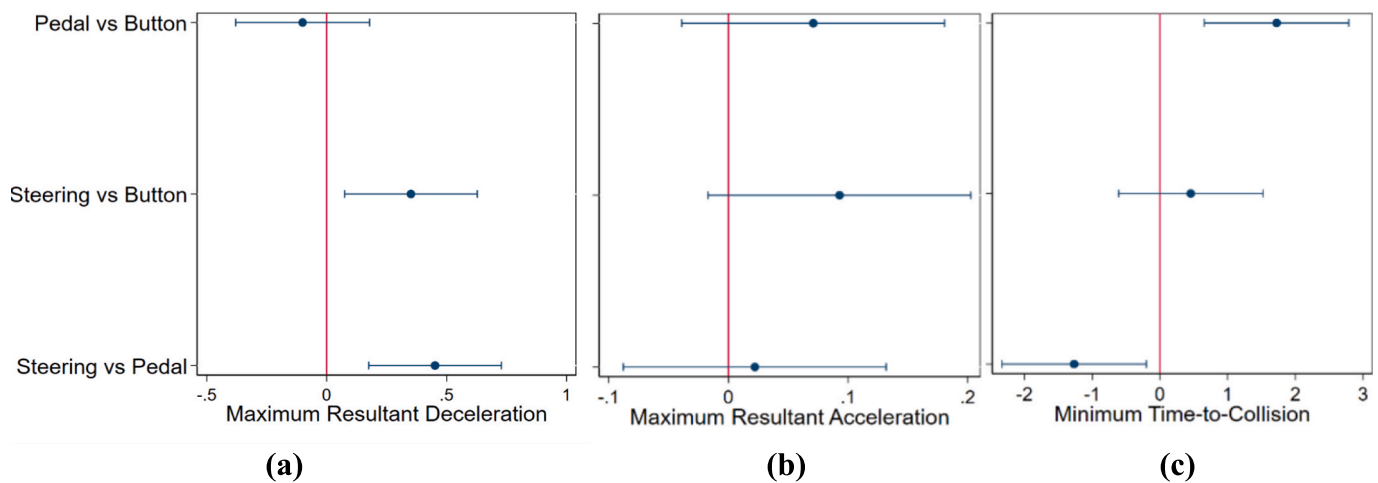


Fig. 7. Pairwise comparison TOC quality and safety between various mechanisms in (a) diverging, (b) merging, and (c) critical situation.

mechanisms should also be investigated in future studies.

AUTHOR CONTRIBUTIONS.

The authors confirm contribution to the paper as follows: study conception and design: M. Bassani, G. Marinelli, A. Hazoor, A. Hassani, A. Karimi; data collection: G. Marinelli, A. Hazoor, A. Hassani; analysis and interpretation of results: M. Bassani, A. Karimi, G. Marinelli, A. Hazoor, A. Hassani; draft manuscript preparation: M. Bassani, G. Marinelli, A. Hazoor, A. Hassani, A. Karimi. All authors reviewed the results and approved the final version of the manuscript.

CRediT authorship contribution statement

Arastoo Karimi: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Arash Hassani Barbin:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing, Software, Visualization. **Arash Hazoor:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing, Software. **Giuseppe Marinelli:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Visualization, Writing – original draft, Writing – review & editing. **Marco Bassani:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

TRAFIKKLAB, Road Traffic Division, NORU University (Norway) is gratefully acknowledged for having financed the research stay of Arash Hassani Barbin during his Master thesis development. This research was made possible thanks to the support of the *Compagnia di Sanpaolo* Foundation, which funded the project: “DIRECTIONS - driver road interaction on future road infrastructures” (No. 2021.2146). A special thanks to Marthe Sumstad for her contribution to the data collection.

Data availability

Data will be made available on request.

References

- AASHTO, 2018. *A Policy on Geometric Design of Highways and Streets*, 2018. AASHTO. Association, W.M., 2024. WMA Declaration of Helsinki—Ethical Principles for Medical Research Involving Human Subjects. <https://www.wma.net/policies-post/wma-declaration-of-helsinki/> [accessed on 10 March 2024].
- Chen, C., Lin, Z., Zhang, S., Chen, F., Chen, P., Zhang, L., 2021. The Compatibility between the Takeover Process in Conditional Automated Driving and the Current Geometric Design of the Deceleration Lane in Highway. *Sustainability* 13 (23).10.3390/su132313403.
- Classen, S., Sisiopiku, V.P., Mason, J.R., Yang, W., Hwangbo, S.-W., McKinney, B., Li, Y., 2024. Experience of drivers of all age groups in accepting autonomous vehicle technology. *Journal of Intelligent Transportation Systems* 28 (5), 651–667.
- Detjen, H., Geisler, S., Schneegass, S., 2020. In: *Maneuver-Based Control Interventions during Automated Driving: Comparing Touch, Voice, and mid-Air Gestures as Input Modalities. and Cybernetics (SMC)*. IEEE, Man, pp. 3268–3274.
- Doubek, F., Loosveld, E., Happee, R., de Winter, J., 2020. Takeover Quality: Assessing the Effects of Time Budget and Traffic Density with the Help of a Trajectory-Planning Method. *Journal of Advanced Transportation* 2020, 1–12. <https://doi.org/10.1155/2020/6173150>.
- Du, N., Zhou, F., Pulver, E.M., Tilbury, D.M., Robert, L.P., Pradhan, A.K., Yang, X.J., 2020. Examining the effects of emotional valence and arousal on takeover performance in conditionally automated driving. *Transportation Research Part C: Emerging Technologies* 112, 78–87. <https://doi.org/10.1016/j.trc.2020.01.006>.
- Gold, C., Damböck, D., Lorenz, L., Bengler, K., 2013. “Take over!” How long does it take to get the driver back into the loop?. In: *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. Sage Publications Sage CA: Los Angeles, pp. 1938–1942.
- Haque, M.M., Washington, S., 2014. A parametric duration model of the reaction times of drivers distracted by mobile phone conversations. *Accident Analysis & Prevention* 62, 42–53.
- Huang, G., Pitts, B.J., 2022. Takeover requests for automated driving: The effects of signal direction, lead time, and modality on takeover performance. *Accident Analysis & Prevention* 165, 106534. <https://doi.org/10.1016/j.aap.2021.106534>.
- Jansen, R.J., Tinga, A.M., de Zwart, R., van der Kint, S.T., 2022. Devil in the details: Systematic review of TOR signals in automated driving with a generic classification framework. *Transportation Research Part F: Traffic Psychology and Behaviour* 91, 274–328. <https://doi.org/10.1016/j.trf.2022.10.009>.
- Kleinbaum, D.G., Klein, M., Kleinbaum, D.G., Klein, M., 2012. Introduction to survival analysis. A self-learning text, *Survival analysis*, pp. 1–54.
- Louw, T., Kountouriotis, G., Carsten, O., Merat, N., 2015. *Driver Distraction During Vehicle Automation: How Does Driver Engagement Affect Resumption Of Control?*, 4th driver distraction and inattention conference. New South Wales, Sydney.
- McNabb, J.C., 2017. *Warning a distracted driver: Smart phone applications, informative warnings and automated driving take-over requests*. Arizona State University. PhD thesis.
- Melcher, V., Rauh, S., Diederichs, F., Widlroither, H., Bauer, W., 2015. Take-Over Requests for Automated Driving. *Procedia Manufacturing* 3, 2867–2873. <https://doi.org/10.1016/j.promfg.2015.07.788>.
- Merlihot, G., Bueno, M., 2022. How drowsiness and distraction can interfere with takeover performance: A systematic and meta-analysis review. *Accid Anal Prev* 170, 106536. <https://doi.org/10.1016/j.aap.2021.106536>.
- Mok, B., Johns, M., Lee, K.J., Miller, D., Sirkin, D., Ipe, P., Ju, W., 2015. Emergency, Automation Off: Unstructured Transition Timing for Distracted Drivers of Automated Vehicles. In: *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, pp. 2458–2464.
- Petermeijer, S., Bazilinsky, P., Bengler, K., de Winter, J., 2017. Take-over again: Investigating multimodal and directional TORs to get the driver back into the loop. *Appl Ergon* 62, 204–215. <https://doi.org/10.1016/j.apergo.2017.02.023>.

- Politis, I., Brewster, S., Pollick, F., 2017. Using multimodal displays to signify critical handovers of control to distracted autonomous car drivers. *International Journal of Mobile Human Computer Interaction (IJMHCI)* 9 (3), 1–16.
- Qiao, L., Li, J., Zhang, T., 2024. Impacts of Training Methods and Experience Types on Drivers' Mental Models and Driving Performance. *International Conference on Human-Computer Interaction*. Springer 44–56.
- Sae, 2021. Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE. International.
- StataCorp, 2017. Stata Statistical Software: Release 15. College Station, TX: StataCorp LLC.
- Tan, X., Zhang, Y., 2022. A Computational Cognitive Model of Driver Response Time for Scheduled Freeway Exiting Takeovers in Conditionally Automated Vehicles. *Human Factors: the Journal of the Human Factors and Ergonomics Society* 187208221143028. <https://doi.org/10.1177/00187208221143028>.
- Tanshi, F., Soffker, D., 2022. Determination of Takeover Time Budget Based on Analysis of Driver Behavior. *IEEE Open Journal of Intelligent Transportation Systems* 3, 813–824. <https://doi.org/10.1109/ojits.2022.3224677>.
- Van Der Laan, J.D., Heino, A., De Waard, D., 1997. A simple procedure for the assessment of acceptance of advanced transport telematics. *Transportation Research Part C: Emerging Technologies* 5 (1), 1–10.
- Weaver, B.W., DeLucia, P.R., 2020. A Systematic Review and Meta-Analysis of Takeover Performance During Conditionally Automated Driving. *Human Factors: the Journal of the Human Factors and Ergonomics Society* 64 (7), 1227–1260. <https://doi.org/10.1177/0018720820976476>.
- Wooldridge, J.M., 2018. Wooldridge, introductory econometrics—A modern approach. China Renmin University Press Beijing, China.
- Wu, C., Wu, H., Lyu, N., Zheng, M., 2019. Take-Over Performance and Safety Analysis Under Different Scenarios and Secondary Tasks in Conditionally Automated Driving. *IEEE Access* 7, 136924–136933. <https://doi.org/10.1109/access.2019.2914864>.
- Wu, H., Wu, C., Lyu, N., Li, J., 2022. Does a faster takeover necessarily mean it is better? A study on the influence of urgency and takeover-request lead time on takeover performance and safety. *Accident Analysis & Prevention* 171, 106647. <https://doi.org/10.1016/j.aap.2022.106647>.
- Wu, Y., Kihara, K., Takeda, Y., Sato, T., Akamatsu, M., Kitazaki, S., Nakagawa, K., Yamada, K., Oka, H., Kameyama, S., 2021. Eye movements predict driver reaction time to takeover request in automated driving: A real-vehicle study. *Transportation Research Part F: Traffic Psychology and Behaviour* 81, 355–363. <https://doi.org/10.1016/j.trf.2021.06.017>.
- Yoon, S.H., Lee, S.C., Ji, Y.G., 2021. Modeling takeover time based on non-driving-related task attributes in highly automated driving. *Applied Ergonomics* 92. <https://doi.org/10.1016/j.apergo.2020.103343>.
- Zeeb, K., Buchner, A., Schrauf, M., 2016. Is take-over time all that matters? The impact of visual-cognitive load on driver take-over quality after conditionally automated driving. *Accid Anal Prev* 92, 230–239. <https://doi.org/10.1016/j.aap.2016.04.002>.
- Zeeb, K., Härtel, M., Buchner, A., Schrauf, M., 2017. Why is steering not the same as braking? The impact of non-driving related tasks on lateral and longitudinal driver interventions during conditionally automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour* 50, 65–79. <https://doi.org/10.1016/j.trf.2017.07.008>.
- Zhang, P., Zhu, B., Zhao, J., Fan, T., Sun, Y., 2022. Performance evaluation method for automated driving system in logical scenario. *Automotive Innovation* 5 (3), 299–310.