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Title:

What Happens when Drivers of Automated Vehicles Take Over Control in Critical Lane Change Situations?

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Abstract

According to legislation, take-overs initiated by the driver must be possible at all times during automated driving. For example, when drivers mistrust the automation to handle a critical and hazardous lane change, they might intervene and take over control while the automation is performing the maneuver. In these situations, drivers may have little time to avoid an accident and can be exposed to high lateral forces. Due to lacking research, it is yet unknown if they recognize the criticality of the situation and how they behave and perform to manage it. In a driving simulator study, participants (N = 60) accomplished eight double lane changes to evade obstacles in their lane. Time-to-collision and traction usage were varied to establish different degrees of objective criticality. To manipulate these parameters as required, participants were triggered to take over control by an acoustic cue. Although this setting does not allow to investigate driver-initiated take-overs as such, it shows what *might happen* if drivers disable the automation and complete the maneuver themselves. The results of the experiment demonstrate that drivers rated objectively more critical driving situations as more critical and responded to the hazard very fast over all experimental conditions. Compared to the automation, however, their behavior was more extreme with respect to decelerating and steering. This impaired driving performance and increased the risk of lane departures and collisions. The results of the experiment can be used to develop an assistance system that supports driver-initiated take-overs.

1. Introduction

During the past few years, much psychological and ergonomic research has been conducted on automated driving. One important issue of this research concerned the transition of control. ‘A transition in automated driving is defined as the process during which the human-automation system changes from one driving state to another…’ (Lu et al., 2016, p. 1). So far, the main focus of most studies has been on transitions initiated by the automation, so-called ‘system-initiated’ take-overs in contrast to ‘driver-initiated’ ones (Lu et al., 2016; Martens et al., 2007; McCall et al., 2016). Only very few studies have been concerned with the latter.

Moreover, the majority of studies focused on take-over situations in which drivers had “sufficient time […] to respond appropriately to the driving situation at hand” (SAE International, 2018, p. 24). For example, a review from Eriksson and Stanton (2017) on 25 studies showed that the most frequently used lead time from a take-over request (TOR) to a critical event ranged from 3 s to 7 s. These values – particularly the higher ones – constitute rather controllable and uncritical conditions. However, it cannot be excluded that take-over situations with shorter times to a critical event occur, e.g. in case of driver-initiated take-overs.

To summarize, research has gathered notable knowledge about drivers’ behavior and performance after *system-initiated* take-over in *uncritical* situations, but little is known about the consequences of *driver-initiated* take-overs under *critical* conditions. But is this issue important at all? We claim that it is for two reasons. First of all, the Amendment of Article 8 of the Vienna Convention on Road Traffic requires that automated functions of a vehicle ‘can be overridden or switched off by the driver’ (United Nations Economic Commission for Europe, 2014, p. 9). Second, take-overs may happen in critical and dynamic driving situations for various reasons. Drivers may intervene at any time because they are startled by an unforeseen event or because they doubt that the automation can manage the current maneuver. If this happens, how well can drivers manage the situation, and how does its criticality affect their take-over behavior and performance?

Roche et al. (2020) investigated transitions from automated to manual control in critical driving situations that required braking. Forty-two participants took part in the experiment. They were travelling in an automated vehicle when another car moved into their lane and started braking heavily. The automation responded immediately and braked to avoid a collision. In this situation, the transition of control took place under varying conditions of objective criticality established by different values of time headway and traction usage, varied by longitudinal deceleration. Although the drivers were fully alert (and not distracted as in most other studies), they worsened the situation by overreacting, i.e., they increased the risk of an accident by very strong decelerations and unnecessary lane changes.

In other driving situations, transitions of control may occur under conditions which require steering. Imagine the driver of an automated vehicle who is traveling on the highway while the automated mode is activated. Suddenly, the vehicle ahead of the driver changes lanes and reveals the view onto a close obstacle in the lane. Two cars have crashed and block the right side of the highway. The automation of the driver's vehicle reacts instantly by steering to evade the obstacle. The vehicle lurches to the left towards the crash barrier. Surprised by the maneuver, the driver intervenes and thus deactivates the automation. But is the steering strong enough or on the contrary too strong? Do drivers try to stay on course or are they struggling to change the direction? In any case, they must cope with demanding, short TTCs and with traction usages, which are more extreme than they are used to. If they fail to manage this situation, an accident can hardly be avoided.

Is the drivers' behavior appropriate for the criticality of the driving situation or do they overreact like in the study by Roche et al. (2020)? If they overreact: in which situations do they need support to avoid the dangerous consequences of their overreactions? To answer these questions, we confronted participants with double lane changes in a driving simulator after short periods of automated driving. As in the study by Roche et al. (2020), different degrees of objective criticality were established by varying time-to-collision and traction usage, here realized by lateral acceleration. For this purpose, participants were triggered by an acoustic cue to take over vehicle control when the intended combination of both parameters was met like in Roche et al. (2020). This was accomplished at a certain point of time, either during the first or the second lane change. Since the take-over was triggered, it must be emphasized that we did not investigate *real* driver-initiated take-overs. Instead, we addressed the question what *might* happen, if drivers took over control under certain critical and dynamic conditions.

1.1 Double Lane Changes and Parameters of Objective Criticality

A double lane change is often used to assess driver performance and the handling of a vehicle (ISO 3888-2, 2011). It is a demanding maneuver that is likely to occur in real traffic when obstacles appear or slow vehicles are traveling in the driver's lane. An analysis of reasons for automation disengagements on public roads revealed that a lane change was one of many reasons why drivers did take back control (Lv et al., 2018). Two kinematic parameters affect the objective criticality of this situation (Hu et al., 2019): time-to-collision and traction usage.

Time-to-collision (TTC) denotes the interval from a certain point of time, e.g. a TOR, until a collision would occur with a reference object. A reference object can be a vehicle ahead if the ego vehicle and the vehicle ahead are on the same course and maintain the same speed (Vogel, 2003) or a hazardous obstacle in the lane (Bosnak & Skrjanc, 2017). TTC is calculated by the quotient of the distance to the reference object $d_{distance}$, the velocity of the vehicle v_{ego} and velocity of the reference object $v_{reference}$ (see Equation 1). The smaller TTC gets, the more critical the situation becomes.

$$TTC = \frac{d_{distance}}{v_{ego} - v_{reference}} \tag{1}$$

Various studies were conducted focusing on the available time for a take-over at the moment of the take-over request, i.e. TTC or time headway (THW). They showed that early take-over requests improved the driver's performance in terms of fewer collisions, fewer lane changes, better lane-keeping, higher time-to-collisions, and more adequate decelerations (Mok et al., 2015; Roche et al., 2020; Roche & Brandenburg, 2018; Zhang et al., 2019). Moreover, subjective criticality and workload were lower and the experienced comfort was higher. However, the findings also indicated that drivers take their time to follow an early TOR, thus increasing take-over time (Roche et al., 2020; Roche & Brandenburg, 2018; Zhang et al., 2019).

Besides TTC, traction usage contributes to the objective criticality of a lane change. Due to the lateral movement during a lane change, lateral forces F_y act on the vehicle (Rajamani, 2011). Together with longitudinal forces F_x, they constitute the actual horizontal force; the numerator in Equation 2. The vehicle is stable as long as the actual horizontal force does not exceed the maximal possible force, which is calculated by the friction coefficient μ_f and the vertical forces acting on the tire F_z. Exceeding the maximal possible force leads to instability of the vehicle and loss of vehicle control. This is the denominator in Equation 2. The relation of the actual and the maximal possible force is called traction usage (TU) or adhesion utilization (Nguyen & Müller, 2020) and characterizes the stability of the vehicle (Rajamani, 2011; see Equation 2).

$$TU = \frac{\sqrt{F_x^2 + F_y^2}}{\mu_f * F_z} \tag{2}$$

The higher TU gets, the more critical the situation becomes because the vehicle approaches the maximal TU-value of 1 from which it gets instable and the driver may lose control. The lateral forces during a lane change vary and depend on the trajectory of the vehicle. A steeper trajectory is characterized by higher lateral forces which in turn lead to higher TU. Until now, no study focused on the effects of traction usage on take-over behavior or performance.

1.2 Research Questions

Automated driving systems are designed to change lanes safely even under critical conditions. However, in case of a driver-initiated take-over, such conditions may turn into a dangerous challenge since average drivers are not used to the high lateral forces that are acting during this maneuver. It is uncertain, how the drivers behave, whether their behavior is adapted to the objective criticality, and whether they are skilled enough to master such challenges.

As stated above, this study investigated *what might happen* if drivers took over control during a double lane change of varying degrees of objective criticality resulting from TTC and TU. In accordance with the study by Roche et al. (2020), three research questions were addressed:

(a) Does the objective criticality impact the *subjective criticality* indicating that drivers can discriminate between different degrees of criticality?

(b) Does criticality influence the *take-over behavior*?

(c) Do drivers deliver an *appropriate performance* when they take over during a lane change or do they increase the risk of an accident by their reaction?

The relation between the constructs that are addressed in these three questions can be illustrated by referring to Fuller's Task-Capability Interface (TCI)-model (2005). The TCl-model assumes that drivers are in control of the vehicle as long as their driving capability is sufficient for coping with the demands of the driving task. However, if the demands exceed this capability, drivers are bound to lose control which might entail an accident. The capability depends on a number of variables, such as the drivers' alertness, their perception of the situation and their skills. To manage a current driving situation successfully, its demands must be correctly recognized and be answered by the appropriate behavior which in turn determines the drivers' performance. In the case of changing lanes, drivers must realize the criticality of the situation and accordingly adjust their behavior in terms of steering torque and steering angle (or even braking). These behavioral parameters constitute the quality of the drivers' performance, including lane departures and collisions in case they lose control.

2 Method

For implementing a double lane change, we used an experimental setting close to the scenario described in the introduction. Participants were traveling in the automated mode following a lead vehicle in front of them. Suddenly, the vehicle changed lanes and revealed the view onto two crashed vehicles in the right lane. The automation of the participant's vehicle reacted immediately by steering to the left to evade the obstacle. Some distance away, construction works in the left lane required the driver to return to the right lane, thus completing the double lane change maneuver. For the systematic variation of objective criticality in this situation, the driver's take-over was triggered at specific points in time when the automation was still in control. At these points, defined values of TTC and TU were obtained (for the specific variation of TTC and TU see 2.4). An acoustic cue, which occurred either during the first or the second lane change, served as trigger.

Our study complied with the tenets of the Declaration of Helsinki (World Medical Association, 1964) and was approved by the ethics committee of the Department of Psychology and Ergonomics, Technische Universität Berlin, Germany.

2.1 Participants

Sixty persons (28 women, 32 men) between 20 and 62 years of age (M = 29.1 years, SD = 9.1 years) participated in the experiment. To ensure that they properly understood the German instructions, they were all German native or near-native speakers. Each of them had been holding a driver license for at least three years (M = 11.3 years, SD = 8.6, Max = 44 years). Thirty-two participants (53 %) reported driving less than 5,000 km per year, nineteen participants (32 %) between 5,000 and 10,000 km, four participants (7 %) between 10,000 and 20,000 km, and five participants (8 %) more than 20,000 km. Each participant received 10 €/hour or course credits as gratification for the experiment. All of them gave their informed consent before the experiment started.

2.2 Driving Simulator

A fixed-based driving simulator of the Department of Automotive Engineering at Technische Universität Berlin served as technical platform for the experiment. The same simulator had been used in the previous study by Roche et al. (2020) to investigate critical brake situations. The simulator consisted of an Audi A4 equipped with a force-feedback steering wheel, active pedals, original control interfaces, and a motion seat. The motion seat was used to generate longitudinal and lateral forces which corresponded to the visual simulation of the driving. The implemented automation matched an automated driving system at SAE-level 3 (SAE International, 2018). It consisted of an adaptive cruise control and a lane-centering system. The threshold for deactivating the automation was set to 18 N of brake pedal force and ± 1 Nm steering wheel torque for less critical TU-conditions, resp. ± 2.5 Nm steering wheel torque for more critical TU-conditions. The different thresholds accounted for the stronger steering of the automation in the more critical TU-trials.

A front view angle of 180° was enabled by three projectors and a curved canvas (see **Fig. 1**). The rear view was realized by one rear projector and a second canvas behind the vehicle. Participants could observe the traffic behind them via the rear view mirror and the left side mirror. The visualization was implemented with SILAB 5.0 from the Würzburg Institute of

Traffic Sciences GmbH (*SILAB*, 2014). The vehicle model was calculated by the commercial driving dynamics program IPG CarMaker 6.0. According to Equation 2, TU was estimated based on the longitudinal and lateral accelerations, gravity, and friction coefficient. The friction coefficient was not varied in this study. For a more detailed description of the driving simulator, see Nguyen and Müller (2019a). The experience of lateral accelerations was conveyed by the dynamic visualization of the driven trajectory and by the lateral tilt of the motion seat. Driving noise was presented via speakers and driving vibrations were transmitted by a subwoofer. To enable the communication between the participant and the experimenter, the vehicle and the control room were equipped with microphones and speakers.

Fig. 1. The driving simulator at the Department of Automotive Engineering at Technische Universität Berlin, Germany.

2.3 Procedure

The experiment consisted of three parts: a familiarization phase of three minutes, a training phase with six trials and an experimental phase with 14 trials. In the familiarization phase, participants drove on a rural road with some curves and little traffic to accustom themselves to the simulator. A passage bordered by traffic cones formed the route for a double lane change in the training phase. The training was split in two parts. First, participants exercised driving and changing lanes manually in two trials. They accelerated the vehicle up to 80 km/h and drove through the passage while keeping the speed constant. At the end of the passage, they braked to a stop. In the second half, participants were introduced to the automated driving system at SAE-level 3 (SAE International, 2018) and received their instructions. They were asked to take their hands off the steering wheel and their feet off the pedals while the automation managed the longitudinal and lateral control. They were informed that they had to take over control when they heard an acoustic signal. As the trial started, the vehicle accelerated up to 80 km/h and drove through the passage. When the acoustic cue sounded, participants took over control. The cue had a base frequency of 1200 Hz and a duration of 0.6 s. It was presented in two trials before the first obstacle and in two more trials before the second obstacle. After the take-over, participants drove through the rest of the passage manually and stopped at its end.

Before the experimental phase, participants were instructed to take over control only when they heard the trigger - but not otherwise - to avoid unwanted or over-hasty reactions. It was emphasized that the take-over should be performed as fast and safely as possible. Each participant completed 14 trials, eight experimental ones and six filler trials in randomized order. It was precluded that more than two filler trials were presented in a row and that a filler occurred as last trial. In each trial, the vehicle drove behind a leading car on a two-lane highway at a constant speed of 80 km/h and with a constant time-to-collision of 2.1 s to the car in front. One to two other vehicles were following the participant's vehicle in the left or the right lane. The color and the model of all cars changed from trial to trial. Participants performed no non-driving related task, because non-distracted drivers are more likely to initiate a take-over. After driving one minute, the lead vehicle performed a first lane change to the left thus revealing the view on two stationary vehicles that had collided in the right lane (see **Fig. 2**). After passing this obstacle, the lead vehicle performed a second lane change, now back to the right, to evade road works ahead (see **Fig. 2**). The obstacles were 100 m apart. Each was 9 m long and 3.7 m wide. The trajectory of the maneuver comprised two symmetric lane changes. The trigger was presented during the lane change either before the first or before the second obstacle. In case the participants failed to take over, the automation completed the double lane change without causing an accident. In addition to the experimental trials, participants experienced six filler trials to reduce the predictability of the situation. In these trials, less critical double lane changes were performed by the automation and no trigger was presented.

At the end of each trial, the participant stopped the vehicle on the hard shoulder and then rated the experienced criticality of the situation by a single item (Roche, 2021). The item was implemented with SoSci-Survey version 3.1 (www.soscisurvey.de) and presented on an iPad 1. When all trials were completed, participants provided demographic information, such as age, gender and driving experience. The whole experiment lasted no more than 1.5 hours, including breaks the participants requested.

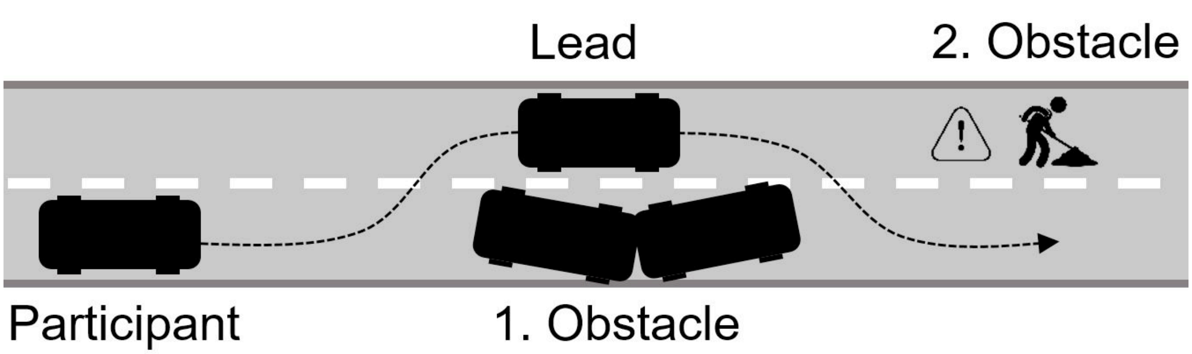

Fig. 2. Schematic illustration of the double lane change.
Note. Two crashed vehicles constituted the first obstacle, construction works the second one.

2.4 Experimental Design and Hypotheses

TTC and TU served as within-subject factors in a 2x2 design. They were used to describe the criticality of the take-over situation. TTC and TU were experimentally varied by the timing of the trigger, i.e. the trigger was presented when the pre-defined values were reached. At this time, the automation was still active and, hence, TTC and TU were independent from the driver's behavior. The lane change was not treated as an independent variable because the two differed in many respects: the predictability of the obstacles (covered by the lead vehicle vs. early visible), the required driver response (steering to the left vs. steering to the right), and the event preceding the trigger (no lane change vs. first lane change). Therefore, data of the two changes were analyzed separately, based on the 2x2 design.

TTC was experimentally varied by the distance between the participant's vehicle and the obstacle at the moment of the trigger. For the first lane change, TTC was calculated regarding the first obstacle, for the second lane change, TTC was calculated regarding the second obstacle. TTC was varied on two levels: 2.1 s (less critical, 46.7 m) and 1.2 s (more critical, 26.7 m). The trigger was presented when the specific TTC-value was met and the automated driving system started the lane change. Therefore, the lane changes with the less critical (longer) TTC started earlier than the lane changes with the more critical (shorter) TTC (see **Fig. 3**).

TU was manipulated by the trajectory driven by the automation. When the automation of the participant's vehicle had to steer more, the trajectory was steeper, hence lateral acceleration and TU were higher (see **Fig. 3**). At the moment of the trigger, TU had one of two values: 0.24 (less critical) and 0.38 (more critical).

Each participant experienced all eight double lane changes, which resulted from the combination of the lane change (first or second), the TTC- (more or less critical), and the TU-values (more or less critical). For the whole lane change, it took the automation 2.25 s from the start of steering until driving straight again if the driver did not take over.

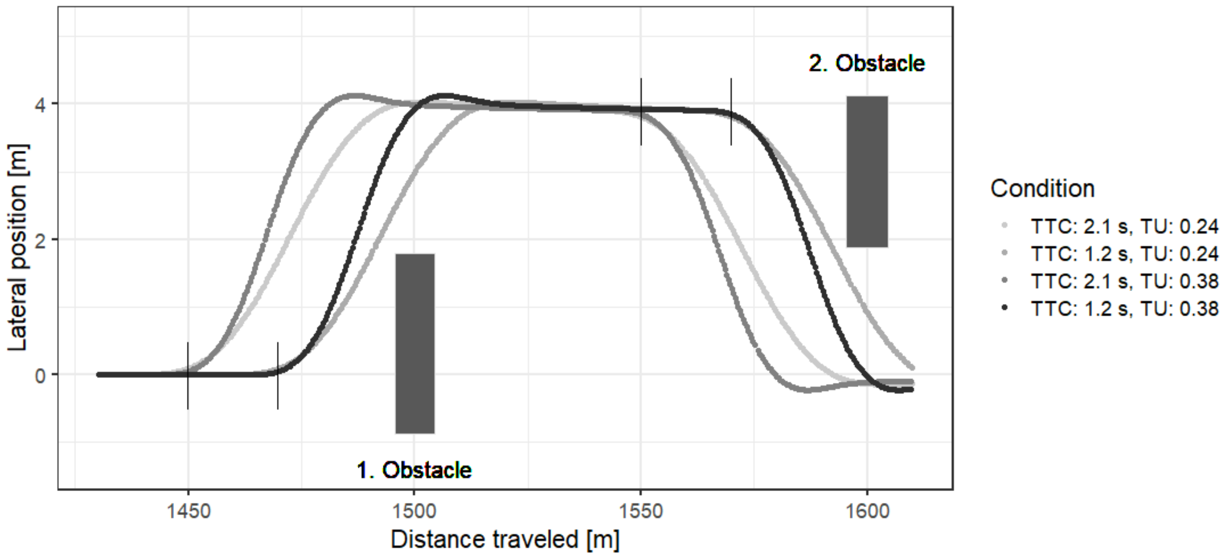

Fig. 3. Lateral position of the participant's automated vehicle.
Note. If the participant had not taken over control, one of the four trajectories would have been driven by the automation, depending on TTC and TU. The vertical solid lines represent the trigger time during the first and the second lane change. The dark grey rectangles represent the locations of the obstacles.

Dependent variables were the criticality rating, take-over time [s], maximal steering wheel angle [°], maximal (longitudinal) deceleration [m/s^2], lane departure frequency [%], and collision frequency [%]. The criticality ratings were assessed by a single-item rating scale ranging from 'not critical' (1 pt.) to 'very critical'[1] (100 pt.). Ten markings were inserted between the endpoints to provide orientation, similar to the NASA-TLX (Hart & Staveland, 1988). The scale had been developed and validated (Roche, 2021) and been used in previous studies (e.g., Roche et al., 2020). It served to answer *research question (a)* by capturing the effect of objective criticality (TTC and TU) on *subjective criticality*.

Take-over time was measured between the trigger onset and the driver's response by steering or braking. For maximal steering wheel angles and maximal deceleration, the highest value during the take-over was extracted per participant and trial. These maxima pointed out the extent of the participants' take-over behavior regarding lateral and longitudinal control. Large

[1] Translated from German ‚sehr kritisch'.

values indicated extreme and hazardous behavior. Strong steering increased the risk of destabilizing the vehicle and heavy decelerating the risk of causing rear-end collisions.

Take-over time, maximal steering wheel angles, and maximal deceleration served to investigate *research question (b).* They represented the *take-over behavior* and indicated how participants reacted to the variations of TTC and TU.

A lane departure was registered when the vehicle crossed the right lane marking by at least 0.5 m. A collision of the participant's vehicle could occur with either the first obstacle, the second obstacle, the crash barrier or the lead vehicle. Lane departures and collisions served as indicators of *take-over performance* in answer to *research question (c)*. Together with overly steering and strong deceleration, they pointed out situations that the driver could not handle adequately.

In line with the results of previous studies (Mok et al., 2015; Roche et al., 2020; Roche & Brandenburg, 2018; Zhang et al., 2019), we hypothesized that more critical conditions with respect to shorter TTCs and higher TUs would lead to higher criticality ratings and more extreme take-over behavior in terms of shorter take-over times, larger maximal steering wheel angles, and larger maximal decelerations. Regarding take-over performance, we expected more lane departures, more collisions as well as stronger steering and deceleration under the more critical conditions. Since we had no prior assumptions whether the two-way interactions between TTC and TU might affect the dependent variables, interaction effects were inspected exploratively.

2.5 Data Analysis

For criticality ratings, take-over times, maximal steering wheel angles, and maximal decelerations, the main effects and two-way interactions were tested with linear mixed-effect models computed with the 'lme4'- package (Bates et al., 2015) in R version 3.6.1 (R Core Team, 2019). We used linear mixed-effect models to analyze the results because they have a higher statistical power when missing values occur than analyses of variances (Kliegl et al., 2011). The assumption of the normal distribution of the residuals was tested with Shapiro-Wilk-test (Field et al., 2012). In case the residuals were not normally distributed, we transformed the dependent variable by Box-Cox-power-transformation with the ‘MASS’-package in R (Venables & Ripley, 2002), log-transformation, square-root-transformation, and cube-root-transformation. Again, we tested with the Shapiro-Wilk-test whether the residuals of the transformed data were normally distributed. When transformed data were used to calculate the model, it is indicated in the corresponding results section and the tables 3 and 6. These analyses were used to answer research question (a) concerning the effects of TTC and TU on criticality ratings as well as research question (b) concerning the effects of TTC and TU on take-over behavior. Logistic models were calculated with the same R-package for the binary variables, i.e. for lane departure and collision frequency. These analyses served to answer research question (c) concerning take-over performance. Degrees of freedom were estimated with Satterthwaite’s method available in the ‘lmerTest’-package (Kuznetsova et al., 2017).

The independent variables TTC and TU were fixed variables and served as linear predictors with the coding of -0.5 for the less critical value and the coding of 0.5 for the more critical one. Due to the centering of the predictors, the intercepts α of the models represent the grand mean (see Equation 4.1). The estimates β_1 resp. β_2 constituted the estimated difference in the criteria when TTC resp. TU grew more critical from the less critical to the more critical value (research question a and b). The estimate β_3 represented the two-way interaction effects of TTC and TU. Besides these fixed effects, a random intercept for each participant γ_j was added to account for interindividual differences and the repeated measurement. Equations 4.2 and 4.3 show the distribution assumptions for the random intercept γ_j and the error term ε_{ij}.

$$Y_{ij} = \alpha + \beta_1 * THW_i + \beta_2 * TU_i + \beta_3 * THW_i * TU_i + \gamma_j + \varepsilon_{ij} \tag{4.1}$$

$$\varepsilon_{ij} \sim N(0, \sigma_{\varepsilon}^{2}) \quad (4.2)$$

$$\gamma_j \sim N(0, \sigma_{\gamma}^{2}) \quad (4.3)$$

Note: Y_{ij} describes the i^{th} measurement of person j for the dependent variable. α reflects the intercept (grand mean), β_1 and β_2 the slopes for TTC and TU, β_3 the estimates for the interaction of TTC and TU. γ_j is the random intercept for each participant and ε_{ij} represents the error term that is not explained by the model.

In case a model failed to converge, the optimizer algorithm 'Bobyqa' (Powell, 2009) from the 'minqa'-package (Bates et al., 2014) was added to the model. The goodness-of-fit is represented by the marginal and conditional coefficient of determination (R^2). The marginal coefficient describes the variance explained by the fixed factors TTC and TU. The conditional coefficient characterizes the variance explained by the fixed and random factors (Nakagawa & Schielzeth, 2013).

In general, extreme steering or deceleration by the driver would cause high TU-values, thus, increasing the risk of losing control over the vehicle and of collisions with passing or following vehicles. These modes of behavior can be interpreted as an overreaction in the course of managing the situation after the take-over. Therefore, the evaluation of the take-over performance (research question c) investigated the appropriateness of steering and deceleration:

- The appropriateness of steering was examined by comparing the participants' maximal values to the calculated maxima that the automation would have reached if no take-over had happened. Two-tailed, one sample t-tests were employed to detect significant differences between these values. The maximal steering wheel angle of the automation amounted to 27.1° for the less critical TU-trials and to 65.4° for the more critical ones[2]. The maximal values of the automation were higher in the more critical TU-trials due to the steeper trajectory in these trials.

[2] The maximal steering wheel angles of the automation were derived from test trials without a driver take-over.

- Since no deceleration was required to avoid a collision, the automation refrained from slowing down under any condition. Accordingly, two-tailed, one sample t-tests were calculated to determine whether the deceleration by the participants differed from 0.

Together, the t-tests on steering and deceleration revealed whether and in which situations participants reacted more extreme than necessary.

3 Results

The results chapter is divided into two sections, one for the first lane change (see tables 1, 2, 3 and **Fig. 4**) and one for the second lane change (see tables 4, 5, 6 and **Fig. 5**).

None of the residuals of the models were normally distributed, except those of the criticality ratings of the second lane change. For most models, the different transformation methods failed to approximate a normal distribution. In these cases, the non-transformed dependent variables were maintained, since model estimates based on non-transformed data are easier to interpret and robust to violations of distributional assumptions (Schielzeth et al., 2020). Only the take-over times in the first lane change and the maximal decelerations in the second lane change were transformed as indicated in the corresponding section.

As mentioned before, data for the first and the second lane change were analyzed separately. For both analyses, trials were excluded when take-overs had occurred either before the trigger or after the participants' vehicle had fully passed the obstacle. Twenty-four experimental trials (5 %) were excluded from the analysis because of missing or too early reactions and six experimental trials (1 %) because of measurement errors. In total, 450 trials (94 %) remained for analysis, 229 for the first and 221 for the second lane change.

3.1 First Lane Change

3.1.1 Subjective Criticality

The analysis of criticality ratings revealed that higher TU led to significantly higher criticality ratings, while TTC did not affect the ratings (see table 3). Also, the two-way interaction of both variables reached significance showing that the effect of TTC was more pronounced when TU was less critical (see **Fig. 4**a). The conditional variance explained by this model was far higher than the marginal variance, hence, a large portion of the variance was explained by the individual tendency of the participants to rate the criticality.

3.1.2 Take-Over Behavior

On average, participants took over after 0.82 s (SD = 0.26, min = 0.45, max = 2.22 s). For the statistical analysis, take-over times were transformed using the Box-Cox-power transformation (λ = -1). Neither TTC or TU nor their interaction had a significant effect on take-over times. In line with this result, the marginal coefficient of the model showed that TTC and TU hardly explained any variance, but rather the random intercept 'participant'.

TTC and TU significantly affected maximal steering wheel angles[3], such that the more critical TTC resp. TU led to higher steering wheel angles (see **Fig. 4**b and **Fig. 4**c).

The analysis of maximal deceleration revealed significant main effects of TTC and TU. With the more critical TTC resp. TU, participants' maximal deceleration was higher (see **Fig. 4**d and **Fig. 4**e).

3.1.3 Take-Over Performance

Lane departures occurred in 27 of 229 trials (11.7 %, see table 1 for detailed frequencies). Only TTC had a significant effect on lane departure probability[4]. Similar to the criticality ratings,

[3] Trials resulting in a lane departure (*N* = 27 trials) or a collision (*N* = 30 trials) were excluded from the analysis of maximal steering wheel angles and maximal deceleration. Including these trials, however, did not change any of the results.

the random intercept ‘participant’ added much to the explanatory value of the model (see the conditional coefficient in table 3). This may be due to the small number of events (four trials) included in the model per participant.

Table 1

Frequencies of lane departures in the first lane change related to TTC and TU.

Lane departure frequency	Less critical TTC	More critical TTC	Sum
Less critical TU	2	6	8
More critical TU	4	15	19
Sum	6	21	27

In 30 of 229 trials (13.1 %), participants collided with the first obstacle (N = 26) or the crash barrier (N = 4), but never with the second obstacle or the lead vehicle (see table 2 for detailed frequencies of TTC and TU). The logistic model with the two-way interaction failed to converge, even when the optimizer was added. Therefore, a model without interaction was calculated. The probability of a collision was significantly higher when TU was more critical. Surprisingly, the collision probability was significantly higher when TTC was less critical.

Table 2

Frequencies of collisions in the first lane change related to TTC and TU.

Collision frequency	Less critical TTC	More critical TTC	Sum
Less critical TU	2	0	2
More critical TU	26	2	28
Sum	28	2	30

[4] Logistic models estimate the probability of an event, e.g. a road departure, based on the observed frequency. Therefore, we use the term ‘probability’ instead of ‘frequency’ when reporting statistical results.

The one sample t-tests showed that the participants' maximal steering wheel angles were significantly higher than those of the automation under three of four experimental conditions (df: 42-54, all $t > 7.0$, all $p < .001$ ***). Only when TTC was less critical and TU was more critical, their steering wheel angles did not differ from the automation. The steering wheel angles of the automation are represented by the horizontal lines in **Fig. 4**b and **Fig. 4**c.

Four one sample t-tests were calculated for maximal deceleration. They demonstrated that, participants decelerated under all conditions (df: 28-54, all $t > 3.5$, all $p < .001$ ***).

Table 3

Summary of statistics for the first lane change: Main effects and interactions of time-to-collision (TTC) and traction usage (TU) on all dependent variables.

Criticality rating [1-100]	Estimate	Std. Error	df	t-value	p-value
Intercept	65.05	2.50	58.28	26.06	< .001 ***
TTC	0.85	1.98	167.98	0.43	.668
TU	22.46	1.99	168.63	11.30	< .001 ***
TTC x TU	-10.54	3.98	168.69	-2.65	.009 **
Variance explained: $R^2_{marginal}$ = 19.9 %, $R^2_{conditional}$ = 66.8 %					N_{trials} = 229

Take-over time [s] (transformed)	Estimate	Std. Error	df	t-value	p-value
Intercept	-0.30	0.03	57.30	-9.57	< .001 ***
TTC	-0.03	0.03	167.53	-1.03	.305
TU	-0.06	0.03	168.48	-1.97	.051
TTC x TU	-0.03	0.07	168.57	-0.40	.693

Variance explained: $R^2_{marginal}$ = 1.3 %, $R^2_{conditional}$ = 42.0 % N_{trials} = 229

Maximal steering wheel angle [°]	Estimate	Std. Error	df	t-value	p-value
Intercept	60.24	1.32	49.28	45.54	< .001 ***
TTC	7.31	1.84	121.02	3.98	< .001 ***
TU	35.47	1.85	126.07	19.13	< .001 ***
TTC x TU	6.87	3.67	119.56	1.87	.063

Variance explained: $R^2_{marginal}$ = 64.2 %, $R^2_{conditional}$ = 74.2 % N_{trials} = 177

Maximal deceleration [m/s^2]	Estimate	Std. Error	df	t-value	p-value
Intercept	2.09	0.17	53.82	12.41	< .001 ***
TTC	1.04	0.28	131.36	3.72	< .001 ***
TU	1.60	0.28	137.30	5.71	< .001 ***
TTC x TU	-0.09	0.56	129.82	-0.17	.866

Variance explained: $R^2_{marginal}$ = 20.1 %, $R^2_{conditional}$ = 31.7 % N_{trials} = 177

Lane departure probability (logistic)	Estimate	Std. Error	z-value	p-value
Intercept	-4.89	3.19	-1.53	.126
TTC	2.57	1.27	2.02	.043 *
TU	1.62	0.92	1.77	.077
TTC x TU	0.75	1.38	0.54	.589

Variance explained: $R^2_{marginal}$ = 10.3 %, $R^2_{conditional}$ = 57.0 % N_{trials} = 229

Collision probability (logistic)	Estimate	Std. Error	z-value	p-value

Intercept	-3.52	0.66	-5.31	< .001 ***
TTC	-3.36	0.87	-3.85	< .001 ***
TU	3.39	0.87	3.91	< .001 ***
Variance explained: $R^2_{marginal} = 38.5$ % , $R^2_{conditional} = 41.1$ %			$N_{trials} = 229$	

Note. The predictors TTC and TU were coded with -0.5 for the less and 0.5 for the more critical condition. Significance symbols: * $p < .05$, ** $p < .01$, *** $p < .001$

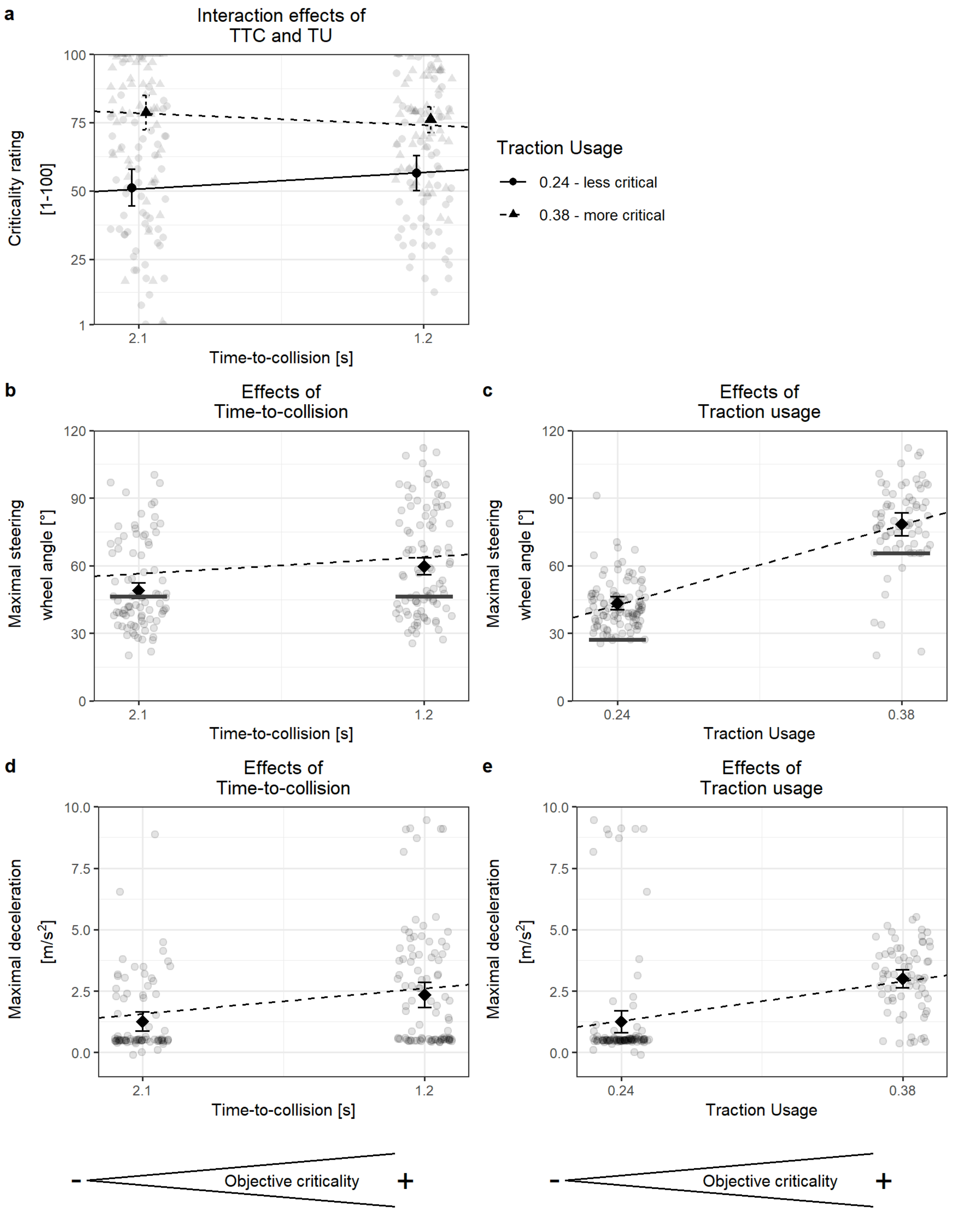

Fig. 4. Result plots of the dependent variables for time-to-collision (TTC), traction usage (TU), and their interactions for the first lane change.

Note. Raw values, means per condition, and regression lines for each dependent variable are plotted. Only significant main effects and interactions are plotted and no main effects in case of a significant interaction. For each plot, the objective criticality increases from left t to right. The dark grey horizontal lines in the plots of maximal steering wheel angles (b and c) represent the maximal steering wheel angles by the automation. Error bars represent ± 1 standard error. A horizontal jitter with factor 0.1 was used to avoid an overlapping of the data.

3.2 Second Lane Change

3.2.1 Subjective criticality

The mean rated criticality was 56.03 pts. (SD = 26.05, min = 1 pt., max = 100 pts.). The model failed to converge, hence, the optimizer was added. The optimized model showed that TTC, TU, and their interaction had a significant effect on criticality ratings. The ratings increased when TTC resp. TU were more critical and the increase due to TTC was more pronounced with the less critical TU (see **Fig. 5**a). Again, the variance explained by TTC and TU was much smaller than the variance explained by those two fixed factors and the random intercept participant (see marginal and conditional coefficient in table 6).

3.2.2 Take-Over Behavior

TTC and the interaction of TTC and TU had a significant effect on take-over time in such a way that the effect of TTC was stronger when TU was less critical (see **Fig. 5**b). However, not TTC or TU but the random intercept 'participant' contributed most to the explanatory value of the model (see marginal and conditional coefficient in table 6).

The analysis of maximal steering wheel angles[5] revealed that they were significantly affected by TTC, TU, and their interaction. More critical TTC resp. TU led to higher maximal steering wheel angles. The effect of TTC was stronger when TU was less critical (see **Fig. 5**c).

The maximal decelerations were transformed using the cube-root-transformation. The maximal deceleration was only affected by TU. Participants decelerated more intensely when TU was more critical (see **Fig. 5**d).

[5] Trials resulting in a lane departure (*N* = 30 trials) or a collision (*N* = 2 trials) were excluded from the analysis of maximal steering wheel angles and maximal deceleration. Including these trials resulted in a highly significant interaction effect of TTC and TU on maximal steering wheel angles, and a significant effect of TTC and an interaction effect on maximal deceleration.

3.2.3 Take-Over Performance

In 30 of 221 trials (13.6 %), participants departed from the road to the right side (see table 4 for detailed frequencies). The model showed that TTC and the interaction of TTC and TU had a significant effect on lane departure probability. More lane departures occurred when TTC was more critical.

Table 4

Frequencies of lane departures in the second lane change related to TTC and TU.

Lane departure frequency	Less critical TTC	More critical TTC	Sum
Less critical TU	1	20	21
More critical TU	4	5	9
Sum	5	25	30

In two of 221 trials (0.9 %), participants collided with the second obstacle ($N = 1$) or with the crash barrier ($N = 1$, see table 5 for detailed frequencies). These occurrences were too few for the calculation of a model.

Table 5

Frequencies of collisions in the second lane change related to TTC and TU.

Collision frequency	Less critical TTC	More critical TTC	Sum
Less critical TU	0	0	0
More critical TU	1	1	2
Sum	1	1	2

Four one sample t-tests on maximal steering wheel angles demonstrated that the mean values differed from the steering behavior of the automation only under one condition ($t(39)$ =

5.245, $p < .001$ ***). Participants' steering was significantly more extreme than that of the automation when TTC was more and TU less critical.

Although no deceleration was necessary to perform the second lane change, participants' average maximal deceleration was 1.34 m/s^2. Four one sample t-tests revealed that this behavior differed significantly from the automation under all conditions (df: 39-56, all $t > 3.5$, all $p < .001$ ***).

Table 6

Summary of statistics for the second lane change: Main effects and interactions of time-to-collision (TTC) and traction usage (TU) on all dependent variables.

Criticality rating [1-100]	Estimate	Std. Error	df	t-value	p-value
Intercept	56.45	2.52	58.31	22.36	< .001 ***
TTC	17.11	2.14	162.40	8.00	< .001 ***
TU	8.27	2.13	162.02	3.87	< .001 ***
TTC x TU	-27.06	4.23	160.18	-6.39	< .001 ***
Variance explained: $R^2_{marginal}$ = 20.3 %, $R^2_{conditional}$ = 65.1 %					N_{trials} = 221

Take-over time [s]	Estimate	Std. Error	df	t-value	p-value
Intercept	0.92	0.03	56.23	28.95	< .001 ***
TTC	-0.16	0.03	160.34	-6.01	< .001 ***
TU	0.02	0.03	159.95	0.57	.566
TTC x TU	0.12	0.05	158.03	2.26	.025 *
Variance explained: $R^2_{marginal}$ = 8.3 %, $R^2_{conditional}$ = 59.0 %					N_{trials} = 221

Maximal steering wheel angle [°]	Estimate	Std. Error	df	t-value	p-value
Intercept	50.77	1.25	57.22	40.56	< .001 ***
TTC	10.93	1.95	146.05	5.59	< .001 ***
TU	29.27	1.95	143.37	15.02	< .001 ***
TTC x TU	-10.00	3.88	139.99	-2.58	.011 *
Variance explained: $R^2_{marginal}$ = 56.4 %, $R^2_{conditional}$ = 64.2 %				N_{trials} = 190	

Maximal deceleration [m/s²] (transformed)	Estimate	Std. Error	df	t-value	p-value
Intercept	-0.85	0.05	57.99	-18.78	< .001 ***
TTC	-0.10	0.07	145.6	-1.44	.152
TU	-0.34	0.07	142.99	-5.06	< .001 ***
TTC x TU	0.17	0.14	139.75	1.26	.208
Variance explained: $R^2_{marginal}$ = 7.2 %, $R^2_{conditional}$ = 26.3 %					N_{trials} = 190

Lane departure probability (logistic)	Estimate	Std. Error	z-value	p-value
Intercept	-2.63	0.46	-5.73	< .001 ***
TTC	1.89	0.65	2.89	.004 **
TU	-0.09	0.65	-0.13	.894
TTC x TU	-3.32	1.30	-2.56	.010 *
Variance explained: $R^2_{marginal}$ = 7.2 %, $R^2_{conditional}$ = 26.3 %			N_{trials} = 221	

Note. The predictors TTC and TU were coded with -0.5 for the less and 0.5 for the more critical condition. Significance symbols: * $p < .05$, ** $p < .01$, *** $p < .001$

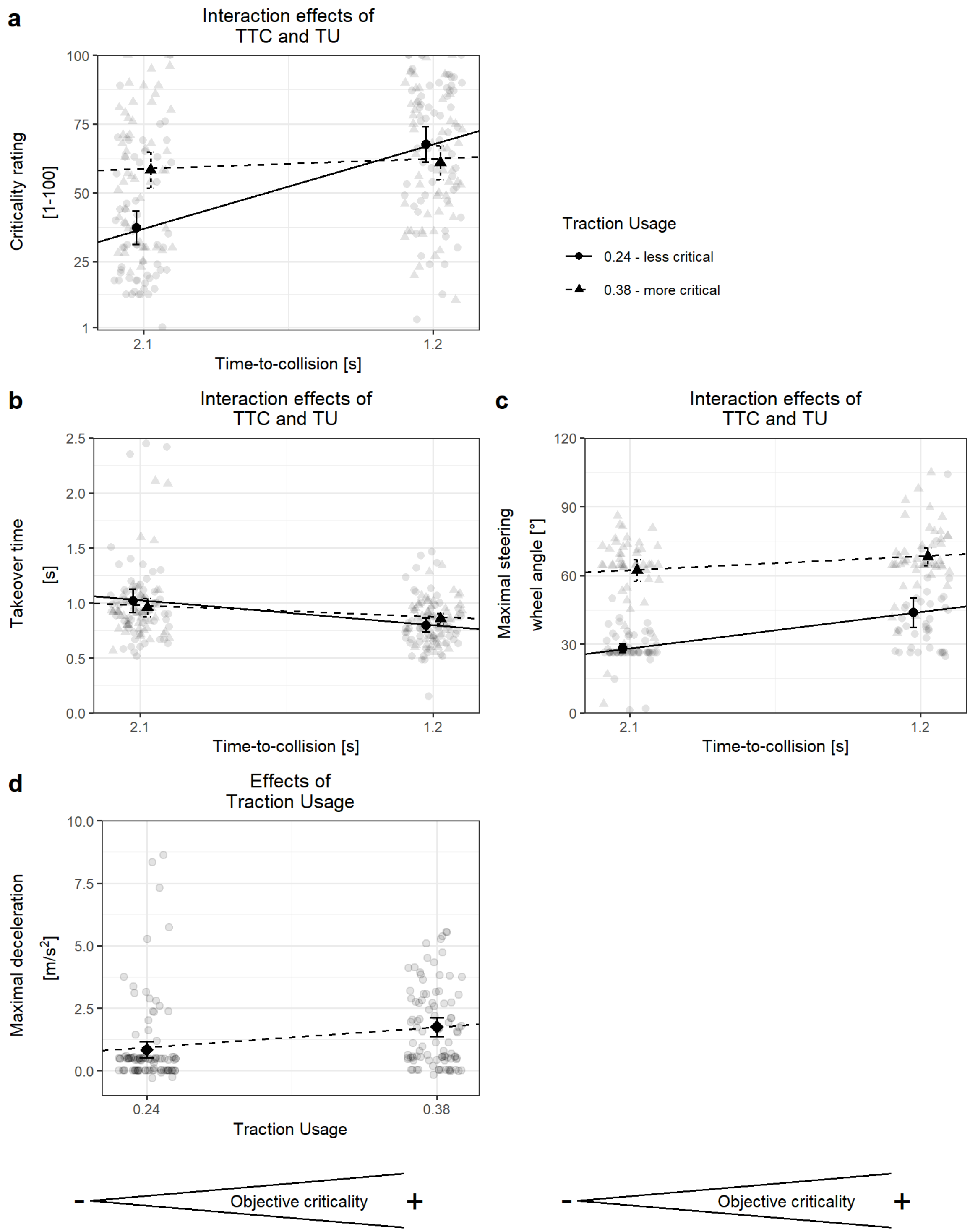

Fig. 5. Result plots of the dependent variables for traction usage (TU) and the interactions TTC x TU for the second lane change.

Note. Raw values, means per condition, and regression lines for each dependent variable are plotted. Only significant main effects and interactions are plotted and no main effects in case of a significant interaction. For each plot, the objective criticality increases from left to right. Error bars represent ± 1 standard error. A horizontal jitter with factor 0.1 was used to avoid the overlapping of data.

4 Discussion

Since drivers must have the option to regain control whenever they wish (United Nations Economic Commission for Europe, 2014), take-overs can happen in any situation. This study explored what might happen if driver-initiated take-overs occur during critical and dynamic double lane changes. We addressed three research questions, investigating (a) whether the objective criticality operationalized by TTC and TU impacts the *subjective criticality*, (b) whether the objective criticality affects the *take-over behavior*, and (c) whether participants show an appropriate *take-over performance*.

When discussing the results, one should keep in mind that the two parts of a lane change were different in various aspects, hence, a comparison is problematic. Besides, it should be noted that the distributional assumption was violated by most models which may limit the reliability of the results.

4.1 Research question (a): Does the objective criticality impact the subjective criticality indicating that drivers can discriminate between different degrees of criticality?

Applying Fuller's TCI-model (2005) to lane changes, the subjective impression of criticality should influence the driver's behavior and behavioral parameters which in turn determine driving performance. The observed significant effects supported this assumption since our participants consistently rated certain situations as more critical than others. However, since the ratings were completed *after* each trial, it cannot be excluded that the participants' success or failure in performing the maneuver also influenced their ratings[6]. To check this assumption, we calculated correlations between criticality ratings and (a) take-over times ($r = -0.212$, $p < .001$

[6] We are grateful to an anonymous reviewer for making us aware of this possibility.

***), (b) lane departures ($r = 0.087$, $p = .067$), and (c) collisions ($r = .245$, $p < .001$ ***). The first significant correlation showed that take-over times decreased when subjective criticality increased, thus supporting the hypothesis that drivers adapted their behavior to perceived criticality. The other two correlations revealed no significant relation between lane departures and ratings but between collisions and ratings. While this result did not falsify the presumed influence of perceived criticality on drivers' performance, it showed that the a-posteriori assessment may have biased the ratings to some extent - at least when there was a drastic consequence involved.

Against our expectations, TTC affected the criticality ratings only in the second lane change, while TU did in the first and in the second one. However, these main effects should be neglected due to the observed interaction effects. A first interpretation of the interactions may be derived from a general characteristic of human attention, i.e., its limited capacity (Kahneman, 1973). When TU was critical, it constituted a hazard which was likely to capture the participants' attention. Since they were suddenly exposed to high changes of lateral forces and to extreme shifts of the optical flow in their field of view, they probably experienced the situation as very intense and menacing. As a consequence, vestibular perception may have dominated visual perception and captured the participants attention. Moreover, the processing of the experienced forces may have required more resources than usual, thus reducing the cognitive capacity for processing stimuli of other modalities, as the visual stimuli resulting from low TTC. On the other hand, when traction usage was less critical, more resources were available for appraising such information. In the first case, drivers may have been almost oblivious of any changes of TTC, while in the second case more capacity should have been available to recognize such changes and process them to judge the criticality of the situation. Hence, TTC could influence the subjective criticality when TU was less critical, but not when it was more critical.

Of course, this is but a preliminary explanation. Together, the two criticality parameters constituted a complex pattern which demands more studies to be fully understood. One branch of related research concerns human perception of hazards. For example, Hu et al. (2019) investigated the effects and interactions of the vehicle's velocity, acceleration (comparable with TU), and distance to an obstacle (comparable with TTC) on passengers' hazard perception. In consistence with our results, they found that the effects of these three parameters were not independent from each other, but interacted and constituted the general impression of a hazard, especially when the velocity was high. However, they did not find a significant two-way interaction of acceleration and distance as we did.

An explanation for the weaker interaction during the first lane change opposed to the second might be derived from the situational context. Due to the restricted visibility of the obstacle during the first lane change, the predictability of the course of events was constrained. Therefore, the situation as such might have appeared as so critical that a smaller TTC did not contribute much more to the experienced criticality. Or in other words, situational characteristics might have overruled the effect of TTC. This was not observed for the second lane change, where the obstacle was visible much earlier.

To summarize, the objective criticality resulting from TTC and TU probably affected the subjective criticality during a double lane change, although the ratings might have been influenced by the success or failure of managing the situation as well. However, the ability to discriminate between less and more critical situations is crucial for acting adequately when taking over control under critical conditions. This leads to our next research question.

4.2 Research question (b): Does the objective criticality influence take-over behavior?

To answer the second research question, the effects on take-over times, maximal steering wheel angles, and maximal decelerations were analyzed.

4.2.1 Take-over times

Under all conditions, take-over times were particularly short. Especially in the first lane changes, our participants responded to the trigger very fast (M = 0.82 s). This might have led to a floor effect obscuring the influence of TTC. The reason for the fast responses was probably the aforementioned sudden occurrence of the first obstacle when the lead vehicle changed lanes and thus generated a very intense stimulus by allowing a clear view on the accident. Based on Davis (1984, p. 288), 'more intense stimuli produce larger responses', i.e., in this case faster take-overs. In contrast, the second obstacle was visible much earlier and the time to react was longer. Now, our participants responded slightly slower (M = 0.92 s). Due to the longer take-over times in the second lane change, differences in TTC could more easily affect take-over times than during the first one. The observed interaction for the first lane change was in line with the interaction for the criticality ratings where the influence of TTC was also more pronounced when TU was less critical. When both findings are viewed together, a consistent picture arises. It shows that an increased subjective criticality coincided with shorter take-over times under the same conditions. This is also supported by the significant correlation between criticality ratings and take-over times ($r = -0.212$, $p < .001$), which we reported at the beginning of section 4.1.

4.2.2 Maximal steering wheel angles

The statistical analysis of both lane changes consistently revealed significant main effects of TTC and TU in both lane changes and an interaction in the second lane change. The shorter time for responding in the more critical TTC-conditions may have impaired the participants' situation awareness, in particular with respect to projecting the future situation, i.e., level three in Endsley's model (1995). Additionally, the short TTC may have appeared as threatening. Since the participants had little time to select and carry out an appropriate action to cope with the threat, they may have selected a steering reaction stronger than necessary to ensure that the obstacles could be definitely evaded. However, no stronger steering was actually necessary to avoid a collision (see the two horizontal lines in **Fig. 4**b). The trajectories of the maneuver under the less and the more critical TTC condition were the same, and so were the required steering angles (see **Fig. 3**).

Since the trajectory was steeper when TU was more critical, a larger steering wheel angle was necessary. This becomes apparent when looking at the maximal angle that was applied by the automation (see the two horizontal lines in **Fig. 4**c). Hence, the behavior of our participants went in the same direction as that of the automation.

The interaction was in line with those for the criticality ratings and the take-over times discussed before. Based on the previous interpretation, it can be assumed again that the steering behavior was more affected by increasing TTC when TU was less critical because participants had more cognitive capacities to appraise the influence of TTC in this case.

4.2.3 Maximal decelerations

A significant effect of TTC on maximal decelerations was observed for the first but not for the second lane change (**Fig. 4**d). This effect might be related to the missing impact of TTC on take-over times during the first lane change. Normally, the smaller TTC should have provoked faster take-overs, but this was not the case. Compensating their rather late response, our participants might have decelerated stronger to avoid a presumed collision.

TU significantly affected maximal decelerations during both lane changes. Interestingly, participants decelerated more when TU was more critical, although a greater deceleration was not necessary to manage the situation.

4.2.4 Conclusion

The reported main effects indicated that the participants' take-over behavior was more extreme when TTC resp. TU were more critical. The effects could be explained by the general finding that more intense and aversive stimuli lead to more intense responses (Davis, 1984), i.e., in our experiment, critical values of TTC and TU caused more pronounced behavior in terms of the aforementioned dependent variables. Even more importantly, all interactions consistently showed that the effect of TTC was more pronounced when TU was less critical. This could be explained by reduced cognitive capacity (Kahneman, 1973) for processing TTC when TU was more critical.

The take-over behavior was more extreme for the first compared to the second lane change (see the intercepts of each dependent variable in table 3 and 6). A reason might be that the obstacle appeared more sudden and thus provoked more intense reactions.

Since some of the behavioral parameters of our participants were stronger than necessary, the question arises whether this implies an impairment of driving performance. This issue is addressed in the next section.

4.3 Research question (c): Do drivers deliver an appropriate performance when they take over during a lane change or do they increase the risk of an accident?

The lane departure frequency, collision frequency, maximal steering wheel angles and maximal decelerations were used to assess whether drivers' take-over performance was appropriate.

4.3.1 Lane departures

In 57 trials (12.7 %), participants departed from the lane. As for the criticality ratings, the take-over times, and the maximal steering wheel angles, the interaction effects of lane departures might be explained by the reduction of cognitive resources (see section 4.1 and 4.2). The effect of TTC was in line with the result that steering wheel angles were larger when TTC was more critical since they increased the probability of departing from the road. This behavior is safety-critical since lane departures are a threat to the driver's safety.

4.3.2 Collisions

In total, 32 collisions (7.1 %) occurred. While only two collisions occurred during the second lane change, 30 collisions were observed during the first one: 26 with the obstacle, four with the crash barrier. It was remarkable that none of the 26 collisions was a frontal one. Instead, our participants collided with the obstacle when they steered back to the right lane and had almost passed it, i.e., in real traffic they would have grazed the obstacle with their right back fender. Those participants who caused this type of accident strived to get back to the right lane as soon as they got aware of the second obstacle at the expanse of checking their surroundings. Indeed, the take-over times in these trials were shorter than in the other trials ($M_{frontal\ collision}$ = 784 ms, $SD_{frontal\ collision}$ = 142 vs. $M_{remaining\ trials}$ = 830 ms, $SD_{remaining\ trials}$ = 273 ms). Turning their head slightly to the right would have sufficed to recognize that it was too early to steer back.

It should be noted that under these conditions, collisions were less likely when TTC was more critical. At first sight, this appears as paradox since usually a short TTC increases the risk of collisions. In this situation however, things were different. To establish the more critical value, the trigger was presented rather late. Therefore, most of the maneuver was carried out by the automation and the vehicle had passed most of the obstacle when the participants took over control. This left hardly any chance to collide with the obstacle even if the participants' response were fast and pronounced.

In addition to TTC, more collisions were observed when TU was high. As discussed earlier, a high TU-value came along with strong lateral forces that might have irritated the participants. Hence, they countered them by strongly steering to the right (compare the main effect of TU on steering wheel angles; Davis, 1984) which – in some cases – led to collisions with the first obstacle. Since collisions necessarily took place *before* a lane departure could occur this might explain the missing effect of TU on lane departure frequency.

To summarize, the total of 32 collisions during a take-over is alarming since *none* would have occurred if the automation had completed the maneuver instead of the driver. The frequencies of lane departures and collisions enable a straight assessment of the driving performance that follows from the behavioral specifics that we have observed. An additional assessment is provided in the following by comparing the maxima of steering wheel angles and of decelerations between drivers and automation.

4.3.3 Maxima of steering wheel angle and deceleration

We investigated whether participants' steering differed from the steering the automation *would have performed* if it had not been deactivated by the participant (values of the automation are indicated by the two horizontal lines in plot **Fig. 4**b and **Fig. 4**c). The results showed that participants steered more extremely than the automation under most conditions during the first lane change and under one condition during the second lane change. Strong steering can lead to collisions with overtaking vehicles, the crash barrier, or the obstacle. It can also cause lane departures or vehicle instability when drivers steer too much and thus further increase TU. Indeed, the mentioned potential consequences of such behavior, i.e. collisions and lane departures, occurred for the first lane change.

While no deceleration was necessary to perform the lane change, participants preferred to decelerate in addition to steering when taking over under critical conditions, especially during the first lane change (see intercepts in table 1 and 2). We observed that participants even decelerated under *all* conditions. Again, this can be qualified as an overreaction because strong decelerations may lead to rear-end collisions with following traffic or may destabilize the vehicle.

4.3.4 Conclusion

The results showed that drivers tended to overreact when they took over control from the automation. Their steering was stronger than necessary and they braked to decelerate although they did not have to. This impaired their driving performance and - in some cases - led to lane departures and collisions.

The results served as a basis for the development of advanced driver assistance systems that support the driver during the take-over process. These systems attenuate too strong steering or braking to avoid collisions or lane departures (Nguyen & Müller, 2019a, 2020, 2019b).

4.4 Limitations

The study had three limitations that should be considered when interpreting our results:

1. Although our research interest concerned driver-initiated instead of system-initiated take-overs, our participants *did not decide themselves* to regain control. Instead, a trigger was used to elicit the transition of control from automation to the driver. This measure was necessary to create comparable lane change conditions with different degrees of objective criticality resulting from TTC and TU. Hence, we did not investigate what *happens* but what *might happen,* when drivers disengage the automation.
2. Since our study investigated critical lane changes, it would have been irresponsible to conduct it under real traffic conditions. Behavior in a driving simulator, however, might deviate from behavior in real traffic. In our experiment, two conditions might have caused such deviations:

- First of all, the driving simulator was static. Even though we used a motion seat to generate longitudinal and lateral forces, it is unclear how well these artificially created forces evoked realistic impressions of motion. However, the car movements were also conveyed by the visual presentation on the screen. The driven trajectory and the speed of the vehicle determined the drivers' optical flow so that lateral and longitudinal movements as well as decelerations and accelerations were visually perceptible. This may have compensated unrealistic vestibular information. Moreover, only two participants suffered from simulator sickness which indicated an adequate consistency of the vestibular stimulation with the visual information.
- Secondly, most of the collisions occurred during the first lane change when our participants steered back to the right lane and contacted the obstacle which they had almost passed. Since the screen of the simulator provided a view of more than 180°, our participants' peripheral perception or a side glance should have enabled them to recognize that it was too early to move back into the right lane. Thus, it seems that the collisions resulted from the drivers' neglect of important visual information. Another factor, however, may have also contributed to the accidents: Since the driver's car was fixed in the simulator and did not really move, our participants may have failed to develop an adequate representation of its length. Hence, it is not certain that drivers would behave the same way under real traffic conditions.

3. Eight similar take-over situations were tested in every session. This was a high frequency compared to realistic traffic conditions. Previous studies have shown that repeated exposure to take-over situations leads to changes in behavior and experience (Roche et al., 2018; Zhang et al., 2019). Over the trials, our participants may have adapted their behavior to the take-over situation by learning when to expect them. Moreover, the repetition of the trigger may have

trained them to respond immediately without spending time on decision making and response selection. Therefore, the small take-over times we observed, may have resulted from our experimental conditions. They are not comparable to take-over times that are system-initiated or to those that occur in real traffic

All in all, the discussed limitations may have biased the results of our study in a certain direction. Since our participants were not distracted by non-driving related tasks, had the chance to form helpful expectations in the course of the experiment, and were trained by successive trials to perform the required response very fast, we may have investigated the *best case* of what might happen, if drivers took over control during double lane changes.

5 Conclusions and Future Work

The research questions and the experimental setting of our study differed from most others on transitions of control. To our knowledge, no one has yet varied TTC and TU to investigate drivers' subjective criticality, behavior and performance during take-overs except for Roche et al. (2020) in their driving simulator study on braking. So, what new insights have been gained by this approach and what follows from them?

The results on double lane changes showed that our participants were probably sensitive for higher objective criticality and appraised the situation accordingly[7]. They succeeded to take over control remarkably fast, but compared to the performance of the automation, the subsequent behavioral pattern carries features of an overreaction.

Comparable results were reported by Roche et al. (2020). The settings and the design of their experiment were the same as those of the present study, except for the investigated maneuver. Again, drivers were aware of different degrees of criticality, took over control very fast

[7] As discussed in section 4.1, the appraisal may have been biased to some extent by the participants' success or failure to complete the lane change flawlessly.

and overreacted. They braked heavier than necessary and changed lanes without cause. Collisions occurred too, but since the brake maneuver was less difficult than the double lane change, the number was much smaller (3 out of 357 trials; 0.8%).

Together the studies on steering and braking demonstrated what *might happen* if drivers took over control under dynamic and safety-critical conditions. In both cases, their behavior was overly pronounced, impaired the driving performance, and increased the risk of accidents (Roche et al., 2020). Since the limitations of both studies were very similar, impairments probably occurred for the *best case* of transitions from automated to manual driving. More severe consequences are to be expected when drivers do not get accustomed to critical take-overs by frequent exposures or when their situation awareness is reduced due to distraction.

Although driver-initiated take-overs can be a threat to safety, the Amendment of Article 8 of the Vienna Convention demands that drivers must be able to overrule the automation and regain control of their vehicle (United Nations Economic Commission for Europe, 2014). Since it would be illegal to thwart driver-initiated take-overs completely as long as this regulation persists, safety can only be increased by an appropriate assistance system. The results of our studies have been used by automotive engineers at Technische Universität Berlin to develop the prototype of such a system. Their general approach is to intervene when TTC or TU reach critical values without suppressing driver-initiated take-overs. Depending on the maneuver, this is accomplished by adjusting the braking force or the steering angle to an appropriate value (Nguyen & Müller, 2019a, 2020).

More research, however, is yet necessary to convert the prototype into a comprehensive assistance system for driver-initiated take-overs. This development should be accompanied by further studies that evaluate the next versions of the system and expand the empirical basis for the assistance. They should investigate whether our findings can be replicated in a dynamic driving simulator or outside the laboratory under safe but physically realistic conditions. Especially experiments doing without a trigger are required to reveal under which conditions *real* driver-initiated take-overs occur.

6 Highlights

- Higher objective criticality in terms of lower time-to-collision and higher traction usage led to an increase of subjective criticality and more extreme take-over behavior in terms of steering and deceleration.
- Drivers took over very fast.
- When taking over during critical and dynamic lane changes, participants steered and braked more than necessary, thus causing lane departures and collisions.
- The data of the experiment contributed to the development of a prototypical assistance system which supports driver-initiated take-overs under critical conditions that require steering, e.g., to evade an obstacle.

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