The Effects of Driving Disengagement on Response Time in Transition to Manual Driving Mode

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Abstract

The article presents an experimental study on the effects of driving disengagement on takeover performance in a simulated driving environment. Takeover performance was measured from participants (N=28, 14 females, age M=30.46, SD =10.67) as the response time (RT) required to complete the transition from automated to manual driving. Several other potential factors for takeover performance were also examined, including driver age, gender, simulator experience, driving-related data, and automotive user interface (UI) complexity (baseline vs. head-up display). A significant effect on RT was found for the type of disengagement (task vs. rest), as well as for the interaction effect of gender and disengagement. Males had significantly longer RT than females (difference in RT: M=2353.14 ms) when engaged in a secondary task. Machine learning was performed to examine the predictive performance of several regression models and the significance of the features (gender, age, driving disengagement, simulator experiance, average speed) on RT. The LightGBM regressor performed well (training accuracy: 0.89, test accuracy: .73, mean absolute error (MAE): .14). In addition to average speed and age, the disengagement features task, rest, and eyes-off-road ratio were the most important predictors of RT.

Keywords

automated driving, engagement, response time, take-over performance

1. Introduction

As automation progresses, drivers become less focused and their situational awareness tends to decrease, especially in highly automated vehicles (HAVs) [1, 2]. Unlike autonomous vehicles, where the vehicle takes control of all driving tasks, in HAVs the vehicle and the driver share control of the vehicle, and the driver takes over the driving task when the vehicle is unable to do so. Since driving in HAV is partially automated, the driver must still be able to regain control of the vehicle within a reasonable amount of time if the automation fails.

This study examines driver performance in a conditionally automated vehicle and in mixed situations (urban and suburban) with changing traffic conditions and obstacles. It focuses on driving disengagement, which is defined as an event where the driver is not involved in driving or is not focused on the driving situation.

The aim of the presented study is to investigate the effects of driving disengagement on driver takeover performance (RT) when taking control of the automated vehicle.

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The effects of different types of driving disengagement (resting vs. completing a non-driving related task (NDRT)) on driver response time to the takeover request are investigated. Specifically, *rest*, *NDRT* engagement, and *eyes off the road* are analyzed as different types of driving disengagement and as possible predictors of driver response time in takeover situations when taking control of the automated vehicle. The effects of two automotive user interfaces are also examined in terms of their complexity (basic instrument cluster (baseline) vs. advanced head-up display (HUD)) and their effects on takeover performance.

In what follows, we briefly present the related work. We then present the experimental setup of the simulated driving environment. The statistical analysis and machine learning are presented in the Results section. The article concludes with a discussion of the results of the presented research and the potential for future work.

2. Related Work

Experimental studies in driving simulators show that user behavior in automated driving poses several risks and safety implications related to takeover performance during the transition to manual driving [3]. As Soares et al. state, ”the takeover performance is the main safety concern related with partial (SAE level 2 (L2) of automation and conditional (SAE level 3 (L3) of automation” [2]. Takeover performance is measured as the time it takes a driver to complete the transition from automated to manual mode and regain control of the vehicle.

To this end, most previous research has focused on takeover requests (TOR) and driver performance (in terms of safety, comfort) when transitioning to manual mode in critical situations where response times (RT) are relatively short, even when the driver is engaged in NDRT [4]. However, studies also show that RT increases when TOR is activated in mixed situations (critical and noncritical) (for a review, see [2]). A study conducted by Eriksson and Stanton showed wide variability in takeover performance, with RT positively correlated with time budget (time available to respond safely) and engagement in secondary tasks [4]. In their meta-analysis of 129 studies of TOR performance in automated driving, Zhang et al. found that RT was correlated with urgency of the takeover situation as well as disengagement (involvement in secondary tasks) [3]. Critical situations yielded a shorter mean RT, whereas involvement in secondary tasks yielded a significantly longer mean RT. Interestingly, there was no consistent effect of participant age on RT.

2.1. The Effects of Disengagement from Driving

The ability to regain control of the vehicle may depend on many factors, both situational (driving conditions, engagement in secondary tasks) and human (age, gender, driving experience). For example, Li et al. investigated the effect of age and driving disengagement on the takeover performance in a driving simulation study (SAE level 3 [5]) with 76 drivers [6]. Among older drivers, driving disengagement and involvement in secondary tasks had a greater effect on RT and takeover quality. However, the results show that 20 seconds is sufficient to take over control from HAV. The authors emphasize that ”age-friendly design of human-machine interaction is important for enhancing the safety and comfort of older drivers when interacting with HAVs” [6]

An interesting insight into driver behavior and disengagement in HAVs (SAE level 3 [5]) has been reported by Wandtner et al. [1]. The authors examined driving disengagement and NDRT task processing as a function of the availability and predictability of automated driving mode (L3). Participants in the study (N=20) completed alternating sections of manual and highly automated driving. The test group had a preview of the availability of the automated driving system in the upcoming sections of the route (predictive HMI), while the control group did not. Participants were free to engage in a secondary task (texting). The results showed that participants in the automated mode accepted more tasks. Drivers accepted more tasks during highly automated driving. Tasks were also rejected more often in the predictive HMI group prior to takeover situations, resulting in safer takeover performance [1]. An important finding of the study is that once drivers are engaged in a task, they tend to focus on completing the secondary task and ignore the TORs. According to the authors, "the results indicate the need to discriminate different aspects of task handling regarding self-regulation: task engagement and disengagement." [1].

3. Methods

3.1. Experimental Design

The study was conducted in a simulated driving environment consisting of a motion-based driving simulator [7] with real car parts (seat, steering wheel, and pedals) and a physical dashboard. The visuals were displayed on three 49-inch curved televisions that provided a 145° field of view of the driving environment. The driving scenario was developed in SCANeR Studio [8]. It spans 13 km (8.08 mi) and simulates a route from a suburban area to a city center. During the driving scenario, there are several intersections with crosswalks. At some of these intersections, pedestrians cross the road, requiring the driver to slow down or stop the vehicle to avoid a collision.

The HUD was assessed for driving a conditionally automated vehicle (SAE level 3 [5]). Participants were informed of the availability of automated driving with a pre-recorded voice message prompting them to turn on the automated driving system (ADS). The ADS could be turned on by pressing a specifically dedicated ADS button on the bottom left lever of the steering wheel. When the ADS became unavailable, the test participants received a visual and auditory takeover notification to take control before the ADS turned itself off. The participants could take over control of the vehicle by pressing on the brake or gas pedal for at least 40 N, steering the wheel for at least 6° or by pressing the ADS button on the bottom left lever of the steering wheel.

Each trial featured four requests to turn on the ADS and four requests to take over control of the vehicle. The requests to take control of the vehicle occurred due to both critical (e.g., a busy pedestrian crossing or complicated intersection) and non-critical events (this was to simulate the vehicle simply losing communication with the infrastructure or the vehicle sensor system failure). The trial always started and ended in the manual driving mode, also referred to by [5] as level 0 (L0) of automation. This resulted in five manually driven intervals and four intervals in automated mode, each lasting approximately 6.5 km (4.04 mi) (half of the total distance). The main task of the test participants was to reach the final destination safely. They were guided there by a navigation system that was part of the HUD interface presented below.

3.2. User Interface

The HUD evaluated in this study was developed based on the results of an exploratory study [9, 10] that provided insight into what and how information should be presented in a HUD for L3 vehicles. The HUD featured elements presented in two dimensions (2D) and using augmented reality (AR). Throughout the journey, the following elements were displayed on the HUD at automation level L0 and L3:

- vehicle speed,
- speed limit,
- speeding,
- available ADAS,
- time to collision < 2 seconds,
- level of automation the vehicle is in (L0 or L3),
- display of important traffic signs 150 m before their location in the environment (stop, yield, pedestrian crossing, etc.),
- GPS directional information directly on the road lane (via AR), and
- short messages.

When automated driving was no longer available, the driver received a visual and auditory takeover request. The visual takeover request was displayed on the HUD 15 seconds before automated driving was turned off with a ”Takeover” sign and a numeric countdown indicating the time remaining until takeover. The auditory takeover request was played 5 seconds before the automation shutdown as a secondary reminder and as an additional notification to draw the driver’s attention to the request. The auditory notification was a pure 4000 Hz tone [11] played at a volume of 65 dB from the start of the takeover notification until the driver took control of the vehicle.

During the takeover request, the HUD displayed the following elements:

- vehicle speed,
- speed limit,
- active ADAS,
- ADL level (L3),
- highlighting important road participants that may affect the takeover using read bounding boxes (via AR),
- visual takeover notification and countdown (15 seconds lead time), and
- auditory takeover notification (5 seconds lead time).

3.3. Participants

Twenty-eight drivers (14 women and 14 men) between the ages of 21 and 57 years (M=30.46, SD=10.67) and with a valid driver’s license (M=11.98, SD=10.24) participated in the study. The participants' only task was to drive the vehicle safely and follow the GPS to reach the destination. Participation in the study was on a voluntary basis, and participants could end their participation at any time. As a thank you for their participation in the study, participants received a €10 gift voucher. The experimental design was prepared according to the rules and guidelines for experiments with human participants issued by University of Ljubljana [12].

3.4. Data

In the presented study, we focus only on the automated driving intervals. The following data are used for statistical analysis.

Dependent variable:

- **Response Time (RT)**. RT is measured (in ms) as the time interval from the request to take over the vehicle (triggered by the visual TOR in UI) to the participant taking over the vehicle in one of the three predefined ways (braking, steering the steering wheel or pressing the ADS button).

Independent variables:

- **Automotive UI**. Two user interfaces with different levels of complexity were compared: Baseline (a typical instrument cluster - a head down physical dashboard, featuring speedometer, tachometer, fuel level indicator and indicator of the level of automation of the vehicle) vs. HUD, as described above;
- **Disengagement**. Disengagement represents events in which the participant was not engaged in driving or focused on the driving situation. Two types of disengagement are compared: Rest vs. Task. Rest vs. Task is binary information. In rest, the participant is not attentive to driving and is not engaged in secondary tasks. If the participant was engaged in both at the time of the individual automated driving interval, the type of disengagement with the longer duration is chosen.
- **Age**. Age is divided based on the age distribution of the participants into two classes: younger drivers (participant age < = 25 years) and older drivers (participant age > 25 years). This selection was first tested to obtain an even distribution of classes.
- **Gender**: male and female.

4. Results

4.1. Statistical Analysis

The Shapiro-Wilk test showed that the dependent variable was not normally distributed ($W=.879$, $p<.001$). Several nonparametric statistical tests were used: Mann-Whitney U test for comparison between two groups, Kruskal-Wallis test for multiple groups, and pairwise Mann-Whitney test for post-hoc analysis (with Bonferroni correction for multiple interactions). Summary statistics of response time (RT) grouped by sex, age, and automotive UI type is provided in Table 1.

Several statistical analyzes were performed to examine the relationship between the independent variables and RT, as shown in Figure 1.

Table 1
Summary statistics: response time (RT), grouped by gender, age, and automotive UI type (UI)

Gender	**Age**	**UI**	**RT (ms)**					
			min	max	mean	sem	std	(95%CI)
Female	older	Baseline	2200	15101	7777.52	1011.49	5057.44	[5795.0, 9760.04]
Female	older	HUD	1801	15149	6992.89	877.77	4644.71	[5272.46, 8713.32]
Female	younger	Baseline	3198	15149	8425.06	1065.32	4392.41	[6337.03, 10513.09]
Female	younger	HUD	3087	15139	7629.5	845.74	3588.17	[5971.85, 9287.15]
Male	older	Baseline	2240	15191	10055.5	968.13	4742.85	[8157.97, 11953.03]
Male	older	HUD	2101	15160	9647.38	907.36	4626.67	[7868.95, 11425.81]
Male	younger	Baseline	1387	15150	8028.54	998.15	5089.61	[6072.17, 9984.91]
Male	younger	HUD	1749	15161	8907.69	1004.10	5119.91	[6939.65, 10875.73]

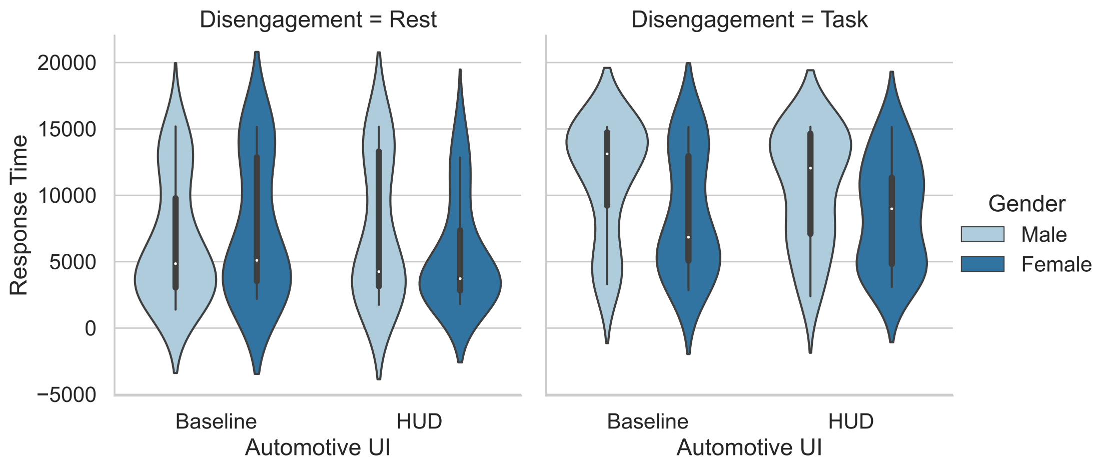

Figure 1: The differences in response time (RT) by the type of automotive UI (Baseline vs. HUD) and gender, separated by the type of disengagement (Rest vs. Task)

Mann-Whitney U tests were performed to examine possible effects of the independent variables on RT. No significant effects were found on RT for age, gender, and the type of automotive UI.

A significant effect on RT was found for the type of disengagement (Task vs. Rest), with the participants engaged in a task having longer RT (U=6294.50, $p < .001$, and effect size CLES=.70).

The analysis also showed a significant effect of the interaction between gender and driving disengagement on RT (H=29.08, $p < .001$). A pairwise Mann-Whitney test was used to analyze the interactions (Bonferroni correction was used for the interactions). A significant difference in RT was found between males (M=10921 ms, SD =4227.13) and females (M=8568.24 ms, SD =4192.73) when engaged in a NDRT ($p < .001$, Hedges' g=-.55). Males had a significantly longer response time than females (difference in RT: M=2353.14 ms).

4.2. Machine Learning: Predicting RT

For machine learning, all continuous features (Task, Rest, Average Speed) were normalized and transformed into a range [0, 1]. The data were split into a training set and a test set ($test_size$=.20)

LightGBM regression was chosen as an advanced machine learning algorithm that makes no assumptions about the normality distribution of the data. The target variable was RT with the following predictors:

- the independent variables used in the statistical analysis (age, gender, type of automotive UI), and additional variables related to disengagement and driving:
- Task (NDRT; duration in ms): a disengagement variable.
- Rest (duration in ms): a disengagement variable.
- Eyes-Off-Road Ratio: a disengagement variable categorized into three levels: low, medium, high.
- Simulator driving experience: 0=Never 1=Once 2=Few times 3=Multiple times. Simulator driving experience might have an effect on RT.
- Average speed in automated mode (ms).
- Timely Transition Count: a count of timely transitions (transition within the 15 second takeover request time before the automation was turned off by the vehicle) to manual driving.
- Reaction: reaction to transition request: 0=none, 1=brake, 2=steer, 3=accelerate, 4=other (e.g. pressing a button on the steering wheel).

The LightGBM model performed relatively well: Accuracy on the training set=.89, Accuracy on the test set=.73, Mean Squared Logarithmic Error (MSLE)=.01, and Mean Absolute Error (MAE)=.14. Figure 2 shows the importance of each feature for predicting RT. The feature importance is calculated with a 'split' method used for tree-based models: the method counts how many times the tree nodes split on each feature, assuming higher importance for the features with more splits. In addition to average speed and age, the disengagement features Task, Rest, and Eyes-Off-Road Ratio were the most important predictors of RT. Interestingly, similar to the statistical analysis above, the type of automotive UI with two different levels of complexity (baseline vs. HUD) did not have a strong influence on RT.

Several other regression models were trained and evaluated. Figure 3 shows their performance based on R^2. R^2 is a goodness-of-fit measure that measures the strength of the relationship the model and the dependent variable on a scale [0,1]. The tree models with similar performance were Random Forest Regressor, Gradient Boosting Regressor, and LightGBM Regressor. These are all ensemble learning models that have better generalizability and thus better predictive performance.

5. Discussion and Conclusion

There are several important findings from the presented research. The results show that engaging in secondary tasks leads to significantly longer RT, which is consistent with several existing studies [1, 3, 4]

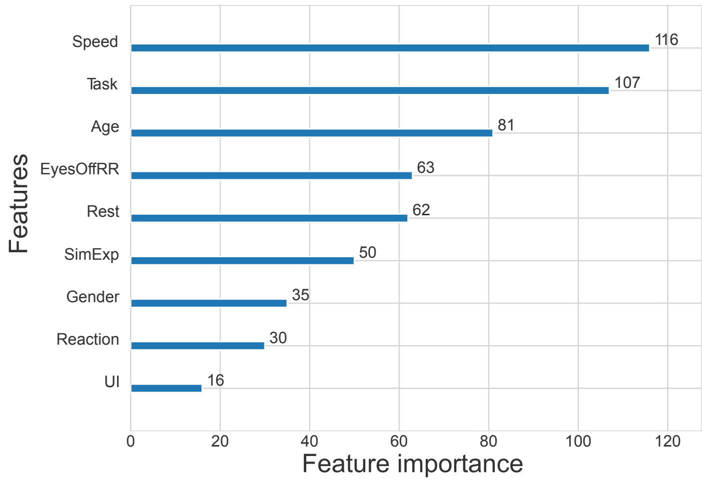

Figure 2: LightGBM Regressor feature importance: the disengagement features Task, Eyes-Off-Road Ratio, and Rest are strong predictors of RT.

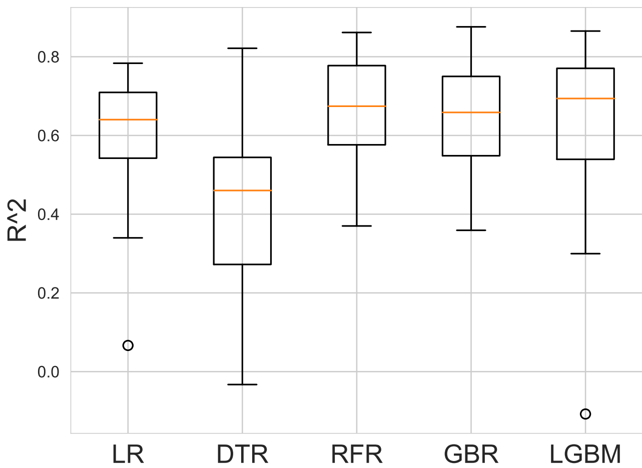

Figure 3: Evaluation of regression models on a test set: LR: Linear Regression, DTR: Decision Tree Regressor, RFR: Random Forest Regressor, GBR: Gradient Boosting Regressor, LGBM: LightGBM Regressor. Reported metric is R^2

The effects of disengagement on RT were found to be significant and men had significantly longer RT than women while engaged in a task. However, no effects were found for age (unlike in[6]) and UI complexity. This could be due to the fact that only automated intervals were analyzed and the effects of both variables could be more pronounced for transition requests from manual to automated mode. As Figure 1 shows, there are differences in RT between men and women while engaged in a task and in baseline UI mode. However, these differences are not significant and could be an effect of the interaction between the type of disengagement and gender.

A comparison of the machine learning models shows that several of them perform well: The Random Forest Regressor, the Gradient Boosting Regressor, and the LightGBM Regressor had similar performance on the testing set. An interesting observation is the predictive performance of age in relation to RT, which was not significant in statistical tests. This might also be due to random effects within and between participants and should be further evaluated in future work.

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