This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

Investigation of the Suitability of a Static Driving Simulator for the Characterization of Lane Departure Avoidance Systems

Sijie Wei, Matthias Becker, Peter E. Pfeffer, Johannes Edelmann

***Abstract*—Simulation-based development is the general trend in the automotive industry, especially for the development of Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) functions. Driving simulators play an essential role in this by providing a reproducible, safe yet realistic environment for research and development, with the ability to rapidly generate almost infinite system and scenario variants. In this paper, a study has been designed to investigate the suitability of a static driving simulator for characterizing a safety-oriented Lane Departure Avoidance (LDA) system through both subjective and objective assessment. The study comprises two components: a subjective assessment conducted with participants and a standardized driver-in-the-loop test drive to objectively assess the system on the simulator. The research endeavors to determine the most suitable test maneuvers for objectively characterizing the system while also identifying target ranges for relevant objective metrics for an optimal subjective assessment. The results show that the professional drivers give a more reproducible subjective rating than the normal drivers. Notably, both groups consistently evaluate subjective criteria that are based on the perception of the steering wheel movement as well as the change in ego position and heading angle. However, the perception of the absolute ego position does not lead to a consistent subjective assessment. This study suggests that the characterization of LDA systems on a static driving simulator is generally feasible, with potential for improvement of characterizing aspects based on absolute positions such as maximum lane overshoot.**

***Index Terms*—static driving simulator, ADAS, lane keeping assistance system, subjective assessment, objective metrics, correlation analysis.**

Acronyms

ADAS	Advanced Driver Assistance Systems.
CF	Curve Follow.
CI	Confidence Interval.
D2CL	Distance to Center Line.
ECF	Extended Curve Follow.
LC	Lane Change.
LDA	Lane Departure Avoidance.
OM	objective metrics.
SA	subjective assessment.
SLR	simple linear regression.
SWT	steering wheel torque.
SWV	steering wheel velocity.

Sijie Wei and Johannes Edelmann are with the Institute of Mechanics and Mechatronics, TU Wien, Getreidemarkt 9, 1060 Vienna, Austria (e-mail: e11946216@student.tuwien.ac.at, johannes.edelmann@tuwien.ac.at). Matthias Becker and Peter E. Pfeffer are with the Department of Mechanical Engineering, Munich University of Applied Sciences, Lothstraße 64, 80335 Munich , Germany (e-mail: becker.matthias@hm.edu, peter.pfeffer@hm.edu).

I. Introduction

As the automotive industry progresses towards safer, more efficient, and autonomous transportation solutions, the need for reliable testing environments has intensified. One crucial tool that has emerged to meet this demand is the driving simulator, a sophisticated platform designed to replicate real-world driving scenarios with a high degree of fidelity.

Driving simulators play a pivotal role in vehicle development, providing a controlled yet realistic environment for testing and refining cutting-edge technologies. These simulators have become integral for researchers to assess the performance, safety, and human-machine interactions of emerging automotive systems.

Moreover, the evolution and validation of ADAS are progressively transitioning into the virtual domain. This paper aims to concentrate on the characterization of the most common and also relevant ADAS, a safety-oriented Lane Departure Avoidance (LDA) System, categorized as Lane Keeping Assistance System (LKAS) Type I according to [1]. The LDA system intervenes only near the lane markings, preserving a relatively wide space around the lane center for the driver's unrestricted maneuvering. The main purpose of this system is to prevent the vehicle from leaving the lane unintentionally, rather than to help the driver stay in the center of the lane (as with LKAS Type II) or to relieve the driver of the task of keeping the lane (as with LKAS with SAE Automation Level 3 [2] or higher).

The characterization of vehicle dynamics with and without ADAS can be divided into various categories, i.e. subjective and objective characterization, objectivization process and further methods such as Naturalistic Driving Data etc. For a thorough literature review on this topic see [3]. However, the subjective assessment of the professional test drivers in the road test can still not be replaced in the series development in the industry to date. One of the reasons is that the relationship between the subjective assessment of the driver and the objective metrics of the vehicle and/or the ADAS is not clear. It is not yet possible to fully represent the driver's subjective opinion with merely objective metrics in the simulation or road test. This is also the reason why the objectivization of driver's subjective assessment is an important research field for the further digitalization of ADAS development. The objectivization of assessments refers to finding a connection in order to link different characteristics of a system and its assessments with human judgement [4]. Although the real road test offers the advantage of customer-oriented real traffic scenarios, virtual tests could also offer several advantages such as reproducibility and efficiency. Especially when we still know little about the mechanism of driver perception of ADAS, it is beneficial to eliminate as many influencing factors as possible, such as traffic, varying road conditions and weather, and focus on the driver's impression of the function itself. The research objective of this paper is to investigate the suitability of a compact static driving simulator for the objective and subjective characterization of an LDA system.

The idea of the driving simulator originally came from the field of pilot training [5]. It provides a safer yet realistic environment and reproducible scenarios for vehicle development, testing and training (e.g. Formula 1 drivers). The basic task of a driving simulator is to reproduce the stimuli of the simulated vehicle acting on the driver as naturally as possible [6]. The structure of a driving simulator contains the underlying vehicle and environment simulation and the simulator hardware components, which consists of a visualization, an audio and a motion system. The driver transmits steering wheel and pedal inputs as control signals to the simulation computer. A vehicle dynamics model calculates the resulting behavior of the vehicle in the simulation based on the environmental simulation with road models. The output signals for image and sound reproduction are also generated in the process. Furthermore, there are diverse possibilities to convey somatosensory information to the driver. These include not only the generation of force feedback on the steering wheel and pedals but also systems that can reproduce vehicle vibrations [7].

[8] classified the driving simulators into 4 categories based on the different levels of technical realization of motion, visual, sound system etc. High fidelity driving simulators in category C and D have the advantage of providing an accurate representation of driving scenarios and a higher degree of immersion. However, they are very costly to purchase and maintain and often take up a relatively large amount of space. Category A and B driving simulators, on the other hand, do not have a motion platform and often have a smaller field of view. However, they are less expensive and easier to set up, sometimes even portable, offering greater flexibility.

However, it is important to be aware of the research purposes for which these static simulators are sufficient and more effective. [9] mentions that static driving simulators are typically suitable for human-machine interaction studies and/or scenarios with constant velocity and large curve radii. The simulation of highly dynamic movements will increase the risk of simulator sickness due to the large deviation between the visual and vestibular channels. An example of the utilization of a static driving simulator in the research Human-Machine-Interface (HMI) is [10].

Since the static driving simulators often have an actuated real steering wheel, they are very suitable for studies which focus on the steering system or the driver's steering/lane-keeping behavior and their interaction with the steering. For example, [11] used the steering characteristic data collected on a static driving simulator to develop a steer-by-wire system to meet individual preference. [12] developed a dynamic control strategy for the steering ratio based on drivers' path-following characteristics using a static driving simulator. Driver's interaction with the vehicle via the steering wheel is also a major objective of research using static simulators. Examples are [13] in the investigation of LKAS with haptic shared control and [14] in the investigation of driver's preferred haptic lane departure warning. [15] studied driver gaze behavior and its relationship to driver steering performance in natural driving. Static driving simulators are also an efficient tool for driver modeling. Because it is efficient to collect driver information and driving measurements in a reproduciable environment without uncontrollable external factors. [16] modeled driver speed tracking behavior, [17] modeled driver's steering behavior, [18] modeled driver visual perception which can help driver assistance systems reduce unnecessary warnings. Driver preferred autonomous driving styles are also investigated in static driving simulators, e.g. [19] and [20].

The transferability of the results on static driving simulators is also discussed. [21] did a validation study on the evaluation of Autonomous Emergency Braking System (AEBS) on a static driving simulator. The authors compared the objective measures of driver behavior and the subjective assessment of the system on the simulator and on a test track and found out that the participants are able to give an evaluation of the system similar to when they are experiencing the AEBS in a real vehicle. In addition, they evaluated the suitability of each objective and subjective measures to assess longitudinal intervening ADAS in a static driving simulator.

Furthermore, researchers have conducted experiments for the purpose of correlation analysis between objective and subjective assessment on a static driving simulator in various fields. [22] investigated the relationship between time headway and a set of subjective ratings for Adaptive Cruise Control (ACC) on a static driving simulator. [23] did a correlation analysis between objective indicators and subjective evaluation in the situation of loss of adherence (LOA) on both a static and a dynamic driving simulator. The authors could explain 2 out of 4 subjective criteria with the objective indicators. The results showed that in general, the regression models obtained with the static simulator explained more variability than those obtained in the dynamic condition. A plausible explanation is that the static simulator gave fewer cues to subjectively assess LOA events and that a simple multiple linear regression model is sufficient to fit the data.

According to the above literature, a static driving simulator has the potential to sufficiently characterize an LDA system due to the low dynamics of the system and its main interaction with the driver through the steering wheel. The objectives of this paper is to investigate the feasability of testing, tuning and optimizing a safety-oriented LDA system on a static driving simulator, taking into account the subjective evaluation of the drivers. For this purpose, it is important to find out which attributes can be perceived subjectively and consistently evaluated, and if the professional and normal drivers evaluate LDA differently. It also has to be identified which test maneuvers and objective metrics are suitable for characterizing LDA. Additionally, this paper attempts to explore the relationship between driver's subjective assessment and the objective met-

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

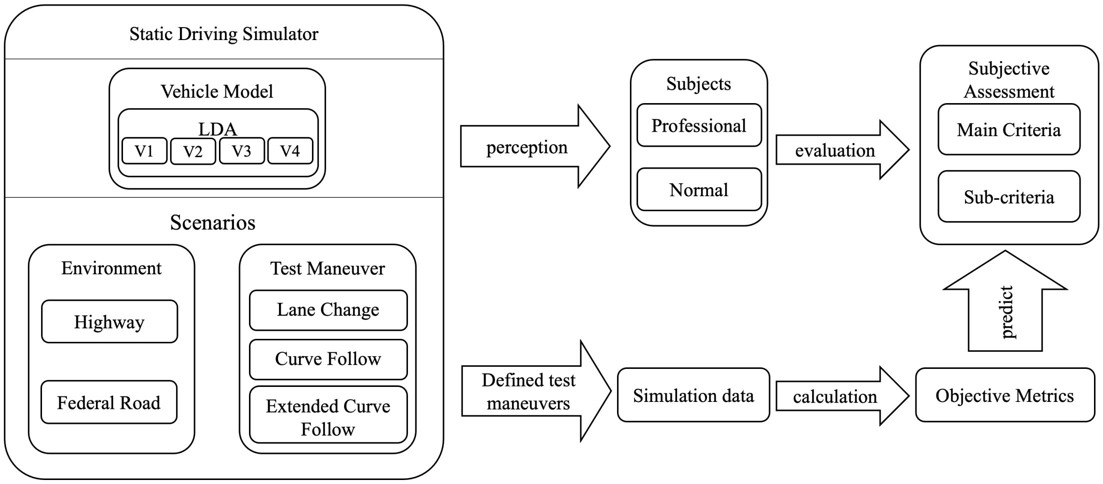


Fig. 1. Experiment design

rics of the system, with the goal of identifying the optimal ranges of the objective metrics.

The remainder of this present paper is organized as follows. Section II presents the study design of a comprehensive investigation of LDA characterization on a medium-fidelity driving simulator. It is demonstrated how data is collected and processed to extract the subjective and objective system assessment and how the relationships between them are investigated. Section III shows the experimental results of the subjective and objective characterization as well as the linear regression analysis of each test maneuver. Section IV provides a detailed discussion of factors such as driver type, subjective and objective criteria in terms of their suitability for characterizing an LDA system on a static driving simulator. Finally, conclusions are made and research questions are answered in Section V.

II. Methods and Data

A. Study design

For this experiment, a fully validated model of a BMW 5-Series vehicle was used in the HiL simulation environment of CarMaker. A generic structure of lateral guidance system of SAE level 2 was designed and then 4 variants of this system were generated by adapting several parameters of the generic model, e.g. parameters of the controller and the intervention strategies. These 4 variants were implemented on the static driving simulator at Munich University of Applied Sciences (MUAS) [24]. They were evaluated both subjectively and objectively with the goal to characterize each variant and to explore their relationship to driver perception. The experiment design is visualized in Figure 1.

Static Driving Simulator at MUAS: The static driving simulator used in this study is illustrated in Figure 2. The input elements of the simulator include a multifunction steering wheel, accelerator and brake pedals. The output elements include a curved widescreen display visualizing the current driving scenario, a second display as an instrument cluster, loudspeakers for driving sound output and a force feedback actuator. A real-time PC pre-processes the input signals and runs a two-degree-of-freedom model of the steering system. It passes inputs such as tie rod displacement to the second processing unit, which runs the vehicle dynamics simulation and sends back the tie rod force. A schematic topology of the setup components and interfaces is shown in Figure 3.

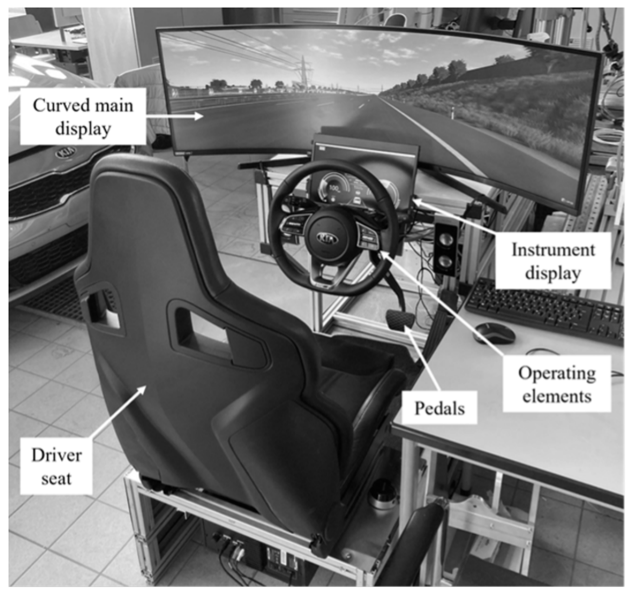


Fig. 2. Static Driving Simulator at MUAS

Subjects: 36 drivers were recruited to take part in the subjective evaluation survey. Only one participant could not finish the whole test process because of motion sickness, whose incomplete ratings were omitted in the data analysis. The evaluation of 2 other participants were not complete and were therefore also excluded from the further analysis. 16 of the rest 33 drivers were professionals from related fields of this study and the rest were normal drivers. There were 5 female and 28 male participants ranging in age from 18 to 53 years (mean 29.6 years, standard deviation 7.4 years). The subjects drive on average 3.4 days per week with a standard deviation of 2.2 days.

8 out of the 33 participants have LDA equipped in their

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

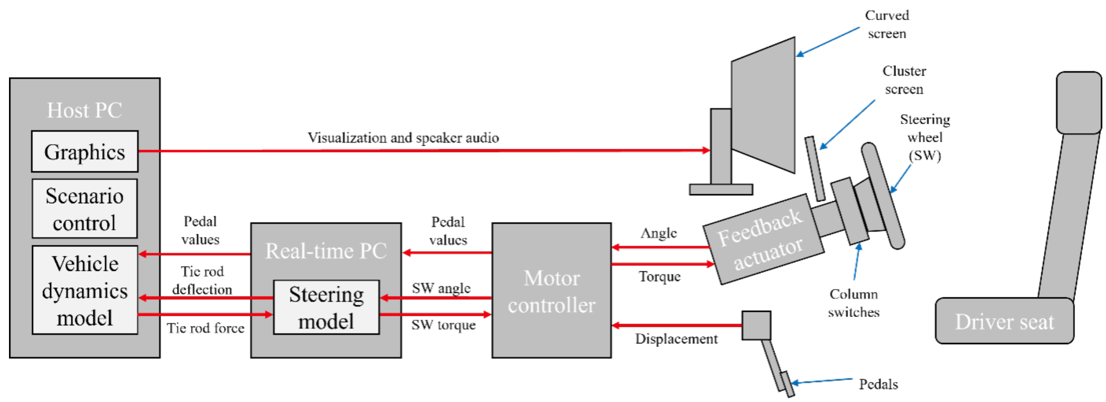


Fig. 3. Static Driving Simulator setup topology

private vehicle. 26 participants never turn the LDA on while driving, 4 use LDA regularly on the highway, 3 regularly on all kinds of road, regardless of whether they have LDA in their private vehicle or not.

Subjective test drive procedure: The participants were asked to virtually test drive the vehicle equipped with an LDA system in the simulator and evaluate each variant by answering a questionnaire. Each participant drove each variant on two different type of roads without traffic - German highway A7 and federal road B19, which were both measured with highly precise Ground Truth technology and implemented in the simulation environment. Thus, each participant undertook 8 test drives in total. They evaluated each variant on different roads after each test drive respectively.

During the test drives, the participants were advised to test the variants by performing several predefined maneuvers at the suitable locations. For example, the participants were asked to perform lane changes without setting the indicator on a straight section in order to test the effort of overriding the system. By pre-defining the test maneuvers, it helps the participants, especially normal drivers who are unfamiliar with driving tests and the road sections, to focus on the relevant characteristics of the system other than reactions caused by other factors, such as different road curvatures. This strategy also helps to minimize the influence of inconsistent execution of the test maneuvers on the subjective evaluation. These predefined maneuvers were however only suggestions for the participants and were not strictly controlled. The participants could also test freely if needed. The predefined test maneuvers are as follows:

Lane Change (LC)

The driver shall conduct a lane change with activated LDA without setting the indicator. During the process, the heading angle and the velocity should be held constant. This test maneuver is defined to test the driver interaction with the steering wheel, for example, if the assisted torque and its build-up and reduction are comfortable and controllable. The maneuver is illustrated in Figure 4a.

Curve Follow (CF)

This maneuver shall be performed on a straight road leading into a curve with constant radius. The driver shall lead the vehicle into the center of the straight with the vehicle parallel to the lane marking before entering the curve. Once the vehicle enters the curve, the driver shall remove the hands from the steering wheel and allow the LDA system to intervene without driver intervention. The maneuver finishes when the first intervention is complete. The maneuver is illustrated in Figure 4b.

Extended Curve Follow (ECF)

This maneuver is similar to Curve Following but conducted on longer curves with larger radius. The preparation of the maneuver is the same as Curve Following. Unlike Curve Following, this maneuver mainly focuses on the continuous intervention behavior of LDA. This means that the maneuver is completed when the system fails to keep the vehicle in its ego lane or when the curve road comes to an end, regardless of the number of interventions.

Subjective evaluation of the system: The evaluation questionnaire was designed in a previous project for a road test with a similar purpose and was adjusted for this simulator study. The subjects were asked to evaluate the system under test (SUT) according to their perception as a driver. The evaluation criteria are subdivided into three main categories - Driver Interaction, Perceived Safety and Functional Performance. Each main criterion is then broken down into several more detailed sub-criteria - the so-called professional criteria, which require higher competence of the driver to sense the fine differences among variants. The subjective assessment criteria used in this study, abbreviated as SA in the remainder of the paper, are described as follows:

- **Driver interaction:**

SA1 Co-Steering: when the LDA intervenes, if it is easy and harmonious for the driver to steer in the same direction as the system.

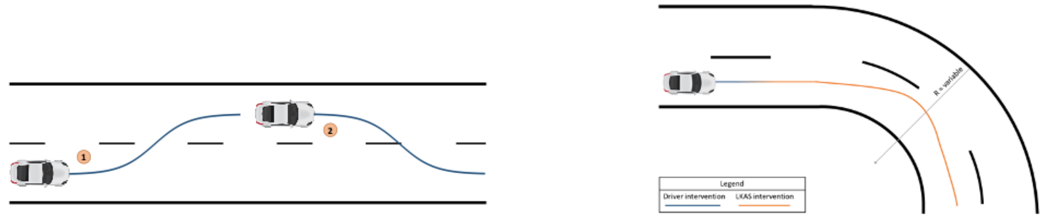
SA2 Counter-Steering: when the LDA intervenes, if it is easy and harmonious for the driver to steer in the opposite direction as the system.

SA3 General Intervention Strength: the overall strength of the steering intervention when the function is engaged.

SA4 Override Capability at Lane Boundary: if it is easy or difficult to override the function during intervention, for example when changing lanes without indicator.

SA5 Harmony of Steering Wheel Movement: how well the steering wheel movement aligns with the driving scenario

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369



(a) (b)

Fig. 4. Test maneuvers. (a) Lane Change. (b) Curve Following.

during an intervention. This criterion assesses if the steering wheel movement is harmonious and appropriately matched to the driving conditions or it is unstable and jerky.

- **Perceived safety:**

SA6 Approach towards Lane Boundary: if the vehicle approaches the lane boundary in a controlled manner after the intervention has started.

SA7 Maximum Lane Overshoot: how far the vehicle exceeds the lane boundary at maximum and if this correspond to the driver's expectation.

SA8 Reliability and Reproducibility: the general reliability and reproducibility of the LDA. It assesses if the response of the system is predictable and reproducible under similar conditions.

- **Functional performance:**

SA9 Control-Free Corridor: the lateral distance of the vehicle from the center of the lane at which the function allows the driver to steer without intervening and if this corresponds to the driver's expectation.

SA10 Returning Behavior: the intensity of the vehicle's lateral response when being guided back to the intended lane, considering the visual cues perceived by the driver, and if this corresponds to the driver's expectation.

SA11 Disengagement Position: refers to the final position of the vehicle in the lane at the end of an intervention. It assesses if the vehicle is positioned at the outer or middle part of the lane, and if it is in line with the driver's wishes.

SA12 Disengagement Angle: refers to the final heading angle of the vehicle with respect to the lane at the end of an intervention. It assesses if the vehicle is positioned parallel to the lane or tilted within the lane, and if it is in line with the driver's wishes.

After rating each sub-criterion SA, the subject gives an overall rating of the main criteria for the category.

The rating scale used in this study is an ATZ 10-point rating scale with uni-polar and bi-polar variants, where a score of 1 indicates unacceptable deficiency and 10 indicates perfection. The bi-polar scale indicates, in addition to the score given to the respective criterion, the direction of the deficiency according to the driver's expectations, where personal preference cannot be universally assumed. For example, uni-polar scale is suitable for evaluating the criterion SA8 Reliability and Reproducibility on the scale of 1 (low) to 10 (high). Meanwhile bi-polar scale is suitable for evaluating SA9 Control-Free Corridor with the additional option to specify whether the free corridor is "too narrow" or "too wide" for the individual driver.

TABLE I
SUBJECTIVE ASSESSMENT CONVERSION

	General Intervention Strength		
	too light	optimal	too heavy
original score	1	10	-1
converted score	1	10	19

Driver-in-the-Loop measurement: In order to characterize the system variants objectively, driver-in-the-loop simulation was carried out in the same simulation environment. The tests were conducted on both measured roads A7 and B19, where the participants evaluated the system subjectively, and synthetic roads such as straight sections and curves with constant radius. The 3 pre-defined test maneuvers described in the previous subjective test drive, which were suggested to the participants, were carried out in the measurement with strictly defined velocity, heading angle etc. The relevant channels are logged for later evaluation, such as ego vehicle state data, relative position and orientation of the vehicle with respect to the lane, steering wheel movement and torque, LDA state and controller data etc.

B. Data Processing

Subjective assessment analysis: The original subjective assessment data with sign were converted into data with a linear scale ranging from 1 to 19 for the further processing. An example is shown in Table I.

After the conversion, the data set needed to be statistically tested. As can be seen from Appendix A, the subjective assessment was not normally distributed. It was then tested if the professional and normal drivers evaluated the system variants in a similar way on a static driving simulator. This was done using the Mann-Whitney U test with the null hypothesis that there is no difference between the distribution of SAs from the two groups. The effect size *Cohen's d* was also calculated according to

$$d = \frac{\bar{x}_1 - \bar{x}_2}{s_{pooled}}, \tag{1}$$

where $\bar{x}_1$ and $\bar{x}_2$ represent the mean value of each group and s_{pooled} the pooled standard deviation for two independent

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

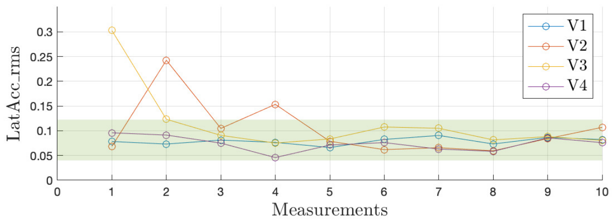


Fig. 5. Comparison of MQI *LatAcc_RMS* among all the measurements

samples. s_{pooled} is defined as

$$s_{pooled} = \sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}}, \tag{2}$$

where s_1, s_2 are the variances and n_1, n_2 the sample sizes of the two groups. $|d| < 0.2$ means a small and $|d| > 0.8$ a large effect [25].

The next step was to investigate whether the drivers could assess LDA consistently on a static driving simulator in general and which factors potentially influenced the drivers' assessment. To answer this question, subjects' driving habit and preferences of the LDA were analyzed. The following factors were included in the n-way ANOVA to analyze their influence on the subjective assessments of the drivers: system variants, road types, driver types and driver styles.

It was found that the professional and normal drivers assessed the system significantly differently (see Section III). Based on this information and the research on previous studies, the SAs were divided into two groups - professional and normal driver. It was also examined if other features of the subjects differ significantly between the two groups, such as driving style, private LDA usage etc., which might bring in more unstable factors if not checked carefully.

Afterwards, a Kruskal-Wallis test was performed in both subject groups to check if the subjects could differentiate the system variants. The significance level was set to $p < 0.1$ according to [26].

Objective metrics of system variants: The simulation data were pre-processed before objective metrics were extracted. First of all, a list of Measurement Quality Indices (MQI) were defined to examine the quality of the measurements. These indices mainly focus on whether all test runs were performed under similar conditions within a reasonable tolerance. For the test maneuver Lane Change, the characteristic values of lateral acceleration, yaw rate, drifting velocity and longitudinal velocity were defined as MQIs. The characteristic values included absolute maximum, standard deviation, root mean square and mean of each signal. Figure 5 shows an example of the MQI *LatAcc_RMS* (root mean square of lateral acceleration during the whole maneuver conduction). Different colors indicate the system variants and each data point represents the MQI value of one test run. The data points outside of the green area are the outliers, the measurement of which are eliminated for further analysis for the lack of comparability.

For each test maneuver, a list of objective metrics, abbreviated as OM in the remainder of the paper, were defined to describe the system characteristic behavior. When defining the OMs, several factors were taken into consideration. First of all, only the signals that are perceivable for the drivers on a static driving simulator were selected. Here, the information about the lateral vehicle motion is perceived solely through the optic sensory channel. According to [27], the eyes can perceive absolute and relative positions (e.g. lateral position in the lane), angles (e.g. yaw angle) and their time derivatives (e.g. yaw rate). However, second and higher order time derivatives such as lateral acceleration and jerk cannot be perceived by the optical channel and were therefore excluded from the OMs. The information about the controlled system in the lateral direction, including the setpoints and state variables, consists of the steering wheel angle and steering wheel torque. These are primarily perceived through the optical, tactile and proprioceptive channels on a static driving simulator and relevant OMs could be derived from them. Secondly, redundant metrics were avoided. For example, during the test maneuver Extended Curve Following, heading angle and drifting velocity of the vehicle are interchangeable at a constant velocity. Therefore, only heading angle was selected for being more dominant in the visual perception. The general rules one should pay attention while defining the objective metrics are discussed in [28].

In the following, the OMs describing the Lane Change maneuver are defined. The abbreviation LC here represents the maneuver name "Lane Change" and LC_OM1 for example the first objective metric of the maneuver Lane Change, i.e. SWT_overpress. In the Lane Change maneuver, which is a closed-loop maneuver, the vehicle shall cross the lane marking with constant speed and heading angle. Here, the system intervention torque and the steering wheel torque as well as movement are in focus. Various characteristic values of these signals were investigated, which are categorized into 3 groups as followed.

Category 1: Torque

This category focuses on the characteristic values of steering wheel torque and the assisting torque generated by LDA.

LC_OM1 *SWT_overpress* [Nm]: Steering wheel torque while the vehicle's Center of Gravity (CoG) is crossing the lane marking.

LC_OM2 *SWT_abs_max* [Nm]: Maximal absolute steering wheel torque throughout the intervention process.

LC_OM3 *mean_intervention_torque* [Nm]: Mean value of the absolute system assisting torque throughout the intervention process.

Category 2: Distance to Center Line (D2CL)

This category focuses on the characteristic values of the Distance to Center Line (D2CL) of the ego vehicle, i.e. the distance from the CoG to the center line of the ego lane.

LC_OM4 *intervetion_pos* [m]: D2CL at the time point of system intervention start.

Category 3: Time to Line Crossing (TLC)

This category focuses the characteristic values of the Time-to-Line-Crossing (TLC) of the ego vehicle.

LC_OM5 *intervetion_TLC* [s]: Time-to-Line-Crossing at the time point of system intervention start.

Category 4: SWT-D2CL

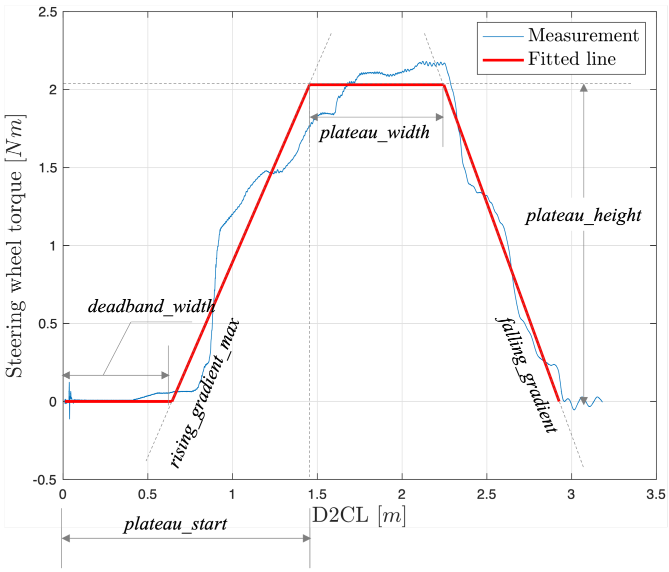


Fig. 6. An example of SWT-D2CL-Curve: steering wheel torque over D2CL while crossing the lane marking

This category includes the characteristic values of the fitted curve of the steering wheel torque over D2CL while crossing the lane marking with LDA intervention. The objective metrics in this category are depicted in Figure 6.

LC_OM6 *deadband_width* [m]: The deadband width around the lane center, where the system does not intervene and the driver can steer freely (calculated based on the fitted SWT-D2CL-Curve).

LC_OM7 *rising_gradient_max* [Nm/m]: The steering wheel torque build-up with respect to the distance to lane marking (calculated based on the fitted SWT-D2CL-Curve).

LC_OM8 *plateau_start* [m]: The relative position of the vehicle to the lane center when the steering wheel torque starts to saturate (calculated based on the fitted SWT-D2CL-Curve).

LC_OM9 *plateau_height* [Nm]: The saturated steering wheel torque when crossing the lane marking (calculated based on the fitted SWT-D2CL-Curve).

LC_OM10 *plateau_width* [m]: The traveled distance where the saturated steering wheel torque is being kept (calculated based on the fitted SWT-D2CL-Curve).

LC_OM11 *falling_gradient* [Nm/m]: The steering wheel torque reduction after the saturated torque has been reached with respect to the distance to lane marking (calculated based on the fitted SWT-D2CL-Curve).

The OM list of the other maneuvers are attached in Appendix B.

The defined OMs were then tested to determine whether they are actually suitable for characterizing the LDA variants on the static driving simulator. Similarly to the SAs, ANOVA test was conducted to examine whether the calculated OMs differed significantly among the variants. The significance level was set to $p < 0.01$.

C. Linear Regression

Once the SAs and OMs were extracted, the relationship between the two needed to be examined. Given the limited number of observations (4 system variants), simple linear regression (SLR) was considered first. Here, SAs were chosen as dependent and OMs as independent variables, whose relationship was modeled by the following equation,

$$\mathbf{y} = \alpha + \beta \cdot \mathbf{x}, \tag{3}$$

where $\mathbf{y}$ represents the array of all the SAs, α and β the regression coefficients, and $\mathbf{x}$ the OMs. Thus, Eq. 3 represents the model function of the LDA system, whose SAs are dependent on their OMs.

However, before the actual modeling, it was necessary to review each possible combination of SA and OM carefully and make predictions about their relationships based on a priori knowledge of the vehicle dynamics and ADAS experts. The aim of this step was to select all the meaningful combinations, as not all possible combinations necessarily make sense. For example, the SA3 General Intervention Strength should not be dependent on the CF_OM5 *final_pos_by_sym* from maneuver Curve Following. This is because the vehicle position where LDA finishes the intervention when following a curve should not influence subject's perception of intervention strength. Table II shows all the possible combinations of SA-OM from maneuver Lane Change, where the 1's mark the meaningful ones.

The SAs and OMs which are not significantly different among system variants according to Kruskal-Wallis and ANOVA test in Section II-B, were excluded for the further analysis. This decision was made because there was not enough evidence showing that these SAs and OMs are suitable for characterizing the 4 LDA variants.

To identify potential redundant OMs, the linear correlation between each OM-pair was investigated. This examined whether the OMs were linearly dependent of each other, which means that the two OMs could contain redundant information. A correlation coefficient $|r| > 0.75$ was selected as the threshold for highly linearly correlated OMs. However, the highly correlated OMs were not directly eliminated for the SLR analysis. This step was more seen as a reference for data reduction. As mentioned in [28], some linearly correlated variables still need to be treated separately in the regression analysis, since the driver might subjectively perceive the signals differently, e.g. lateral acceleration and lateral jerk.

Mean values were calculated for the pre-selected SAs and OMs, based on which SLR is performed. A p-value smaller than 0.1 was defined for a significant regression model. In addition, it was tested if the effect size of the regression model according to Cohen was greater than 2. The effect size *Cohen's* f [25] can range from 0 to ∞ and is calculated by

$$f = \sqrt{\frac{R^2}{1 - R^2}}, \tag{4}$$

where R^2 is the Goodness of Fit of the regression model. The effect size shows how much of the total variance of the dependent variable is accounted for by the independent variable. Cohen defined $f = 0.1, 0.25, 0.4$ as small, medium and large effect respectively [25].

TABLE II
SA-OM COMBINATIONS FROM TEST MANEUVER LANE CHANGE

				SA											
				Co-Steering	Counter-Steering	General Intervention Strength	Override Capability at Lane Boundary	Harmony of Steering Wheel Movement	Approach towards Lane Boundary	Maximum Lane Overshoot	Reliability and Reproducibility	Control-Free Corridor	Returning Behavior	Disengagement Position	Disengagement Angle
OM	Torque	1	SWT_overpress	1	1	1	1	1	1	1		1	1	1	1
		2	SWT_abs_max	1	1	1	1	1	1	1		1	1	1	1
		3	mean_intervention_torque	1	1	1	1	1	1	1		1	1	1	1
	D2CL	4	Intervention_pos		1	1	1	1	1	1		1			
	TLC	5	Intervention_TLC		1	1	1	1	1	1		1			
	SWT-D2CL	6	deadband_width	1	1	1		1	1	1		1	1	1	1
		7	rising_gradient_max		1	1	1	1	1			1			
		8	plateau_start		1	1		1	1	1		1			
		9	plateau_height	1	1	1	1	1	1	1		1	1	1	1
		10	plateau_width		1	1	1								
		11	falling_gradient	1		1	1	1		1		1	1	1	1

Due to the nature of the study, the number of observations for the regression analysis was limited. To test the robustness of the regression models found, the method suggested by [26] was applied in the next step. Besides the mean value of the SAs, the upper and lower boundary of the 90% Confidence Interval (CI) of the SAs were also used for the regression analysis. This means each variant had 3 characteristic values in each SA (lower boundary of 90%-CI, mean, upper boundary of 90%-CI), which made it up to $3^4 = 81$ possible combinations of the dependent variables. An SLR model was calculated for each possible combination, where only the significant models ($p < 0.1$) were saved and the rest were discarded. This resulted in a bundle of regression lines for each SA-OM, which could assist identifying if the found SLR models are robust. For example, the SLR model was not considered robust if the regression line bundle is sparse or does not even have a uniform trend (different signs of coefficient β), which means that the linear regression model found based on SA mean values does not necessarily hold within the 90%-CI of the SA.

The method described in this section is illustrated in Figure 7.

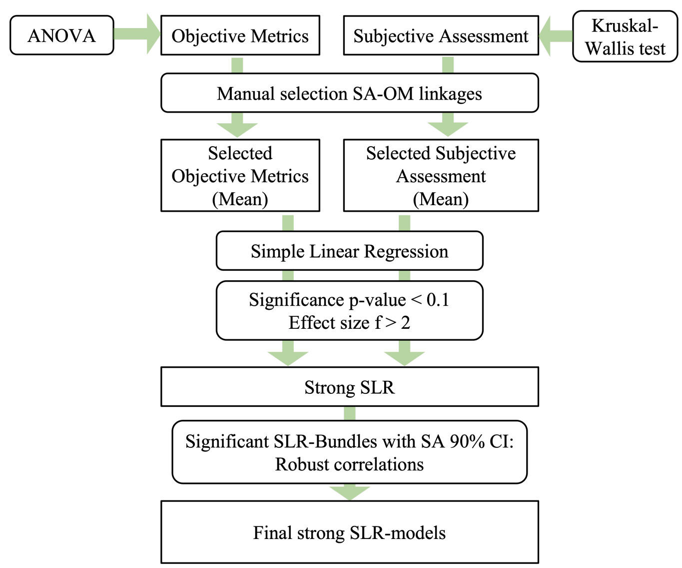


Fig. 7. Flowchart of the applied method for data analysis

III. RESULTS

A. Analysis of Subjective Assessment

Subjects were asked about their own driving style and their preferred driving style as a passenger. While the driving styles of the subjects are relatively evenly distributed, the preferred styles from a passenger's perspective show a clear trend. 23 out of the 33 subjects prefer a comfortable driving style as passenger and only 3 prefer a sportive style. In addition, subjects also ranked the 3 criteria for LDA, safety, comfort and driving pleasure, from the most to the least important. 27 subjects rate safety as the most important criterion, the remaining 6 rate comfort, and none rates driving pleasure as the most important. The results are demonstrated in Figure 8.

The SAs are divided into two groups, namely professional and normal drivers, to investigate their potential differences. The comparison of the SAs of the two groups is shown in Figure 9 and Table III. The difference between the two groups is tested using Mann-Whitney U test, a non-parametric variant of t-test. The null hypothesis that the distributions of both groups are identical can be rejected with $p < 0.01$. This indicates a significant difference between the shape of the two distributions. It can be seen from Figure 9 that the normal

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

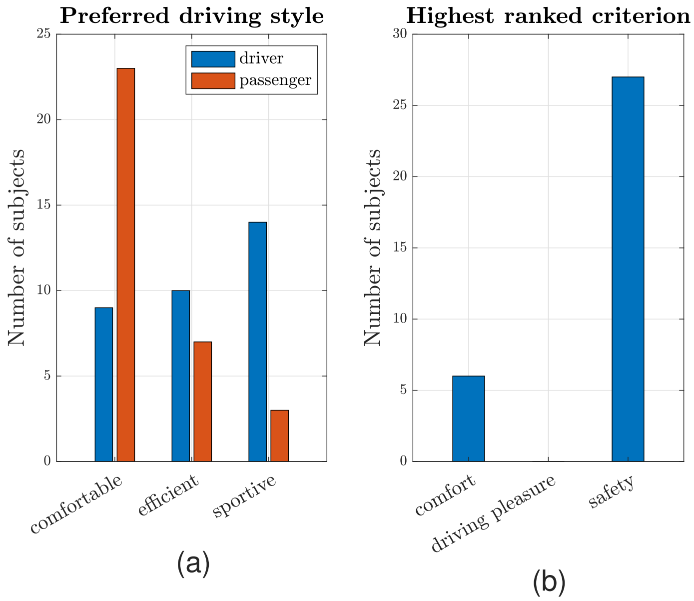


Fig. 8. (a) Preferred driving style from driver's and passenger's perspective respectively. (b) Highest ranked criterion for LDA.

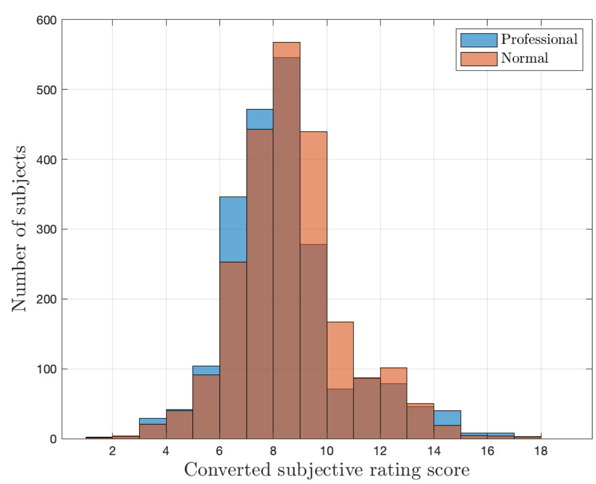


Fig. 9. Distributions of SAs by professional and normal drivers

drivers are more likely to rate higher than 8 in both positive and negative directions (corresponds to the range [8,12] in Figure 9 for the converted scale according to Section II-B). This reflects that the professional and normal drivers use the rating scale differently. However, the two groups have the same median. Furthermore, the effect size *Cohen's d* is too small to indicate a relevant difference between the mean of the two groups.

TABLE III
COMPARISON OF SAS BY PROFESSIONAL AND NORMAL DRIVERS ($p^{**} < 0.01$)

Driver type	median	mean	std	Mann-Whitney U test p-value	Cohen's d
Professional	8.00	8.00	2.21	$1.20e-7^{**}$	-0.09
Normal	8.00	8.20	2.10		

TABLE IV
RESULTS OF N-WAY ANOVA FOR SAS ($p^{**} < 0.01$)

Factors	p-value
LDA variant	0.0052**
Road type	0.7373
Driver type	0.0079**
Driver style	0.0000**

In the next step, n-way ANOVA test is applied to test how the drivers' SAs are influenced by different factors. Four factors being investigated and their p-values are shown in Table IV.

The results show that the subjects evaluated the 4 LDA variants significantly differently. Driver types and their own driving style both have a significant influence on the SAs. On the other hand, the road types where the test drives were conducted, i.e. highway or federal road, do not have an influence on subjects' assessment.

The SAs are divided into two groups, professional and normal drivers, for the further analysis. It is then tested whether the main categotical characteristics of the two groups are significantly different, which could introduce other influencing factors other than driver type. As can be seen from the results in Table V, the listed factors do not have a significant influence on the SAs evaluated by different driver types, including the preference of the system variants. It can be concluded that the difference between the SAs of professional and normal drivers in this study is mainly due to their different level of system understanding and experience in driving tests.

In the following, the SAs are examined individually with the aim of identifying those suitable for characterizing LDA on a static driving simulator. Kruskal-Wallis test is applied for both driver groups on both road types respectively with the null hypothesis that the SA of the 4 variants originate from the same population. The test results of the SAs introduced in Section II-A, evaluated by professional and normal drivers on highways (HW) and federal roads (FR) respectively, are shown in Table VI. 21 out of the 60 null hypotheses can be rejected with a significance level of $p < 0.1$. For 3 sub-criteria, the null hypotheses can be rejected in all test groups, i.e. for both professional and normal drivers on both road types. This means these 3 sub-criteria can be distinguished among 4 system variants consistently independent of driver or road types, which are SA3 General Intervention Strength, SA4 Override Capability at Lane Boundary and SA10 Returning Behavior. Other SAs did not consistently show significant difference among the system variants. A further n-way ANOVA test for these 3 SAs shows that the road types, driver types as well as the driver styles do not have a significant influence on the SAs, but only the system variants. It can be concluded that these 3 SAs are robust criteria that are suitable for characterizing the LDA systems on a static driving simulator, since they can be consistently evaluated independent of road conditions or driver experience and preference.

Regarding the main criteria, only professional drivers can distinguish the variants on highways, i.e. SA-I Driver Interaction, SA-II Perceived Safety and SA-III Functional Performance.

TABLE V
RESULTS OF MANN-WHITNEY U TEST ON THE CHARACTERISTICS BETWEEN PROFESSIONAL AND NORMAL DRIVERS ($p^{**} < 0.01$)

Categorical Variables	**Mann-Whitney U Test p-Value**
General LDA usage (regularly on highways/regularly on all road types/never)	0.5960
Driving style as driver (comfortable/efficient/sportive)	0.7004
Preferred driving style as passenger (comfortable/efficient/sportive)	1.0000
Highest ranked criterion for LDA (comfort/driving pleasure/safety)	0.9570
Best system variant on highway (V1/V2/V3/V4)	0.1887
Best system variant on federal road (V1/V2/V3/V4)	1.0000

TABLE VI
RESULTS OF KRUSKAL-WALLIS TEST ON THE SAS OF THE SYSTEM VARIANTS ($p^{*} < 0.1$, $p^{**} < 0.01$)

		Sub-criteria												Main criteria		
		1	2	3	4	5	6	7	8	9	10	11	12	I	II	III
		Co-Steering	Counter-Steering	General Intervention Strength	Override Capability at Lane Boundary	Harmony of Steering Wheel Movement	Approach towards Lane Boundary	Maximum Lane Overshoot	Reliability and Reproducibility	Control-Free Corridor	Returning Behavior	Disengagement Position	Disengagement Angle	Driver Interaction	Perceived Safety	Functional Performance
HW	Professional Driver	0.63	0.29	0.06*	0.01**	0.40	0.34	0.30	0.09*	0.46	0.00**	0.01**	0.42	0.10*	0.02*	0.05*
	Normal Driver	0.62	0.31	0.07*	0.00**	0.55	0.10*	0.68	0.71	0.05*	0.02*	0.99	0.35	0.70	0.80	0.40
FR	Professional Driver	0.58	0.86	0.02*	0.01**	0.57	0.83	0.40	0.24	0.04*	0.00**	0.07*	0.40	0.60	0.20	0.50
	Normal Driver	0.65	0.10	0.00**	0.06*	0.96	0.47	0.59	0.49	0.25	0.05*	0.50	0.78	0.50	0.30	0.20

TABLE VII
ANOVA RESULTS FOR OMS OF TEST MANEUVER LANE CHANGE ($p^{**} < 0.01$)

Group	**#**	**Objective Metric**	**p-Value**
Torque	1	SWT_overpress	0.0000**
	2	SWT_abs_max	0.0000**
	3	mean_intervention_torque	0.0000**
D2CL	4	intervention_pos	0.4102
TLC	5	intervention_TLC	0.6379
SWT-D2CL	6	deadband_width	0.0018**
	7	rising_gradient_max	0.1541
	8	plateau_start	0.7406
	9	plateau_height	0.0000**
	10	plateau_width	0.7668
	11	falling_gradient	0.0061**

B. Analysis of Objective Metrics

The OMs defined in Section II-B are calculated for each measurement and the mean value is extracted for each system variant. The suitability of the OMs to characterize the LDA variants is tested by ANOVA test. The null hypothesis for each OM to be tested here is that the OM values of the 4 variants originate from the same population. The results for the test maneuver Lane Change is demonstrated in Table VII.

The null hypothesis for LC_OM4, LC_OM5, LC_OM7, LC_OM8 and LC_OM10 cannot be rejected, which are grayed out in Table VII. This means that these metrics do not differ significantly between the 4 system variants, making them unsuitable for objective characterization of the SUT. These OMs are excluded from the further regression analysis for a better robustness of the results.

C. Analysis of Regression Models

After examining the SAs and OMs, the remaining combinations of relevant SA-OM are further analyzed in terms of their relationship. The goal of the regression analysis is to answer the question of how the subjective assessment correlates with the objective metrics and to identify the optimal range of objective metrics preferred by the driver.

1) Results of Lane Change Maneuver: As shown in Table II, there are 17 relevant combinations of SA-OM. For each SA-OM pair, a simple linear regression model is fitted and model quality tested. As described in Section II-C, the SLR model is built based on the mean values of SAs and OMs of each variants. The regression models with a p-value smaller than 0.1 are considered significant.

There are 3 significant SLR models found for the test maneuver Lane Change, which are SA3-LC_OM11, SA4-LC_OM11 and SA10-LC_OM1. The measured data points and the fitted regression lines are shown in Figure 10. The abscissa axis shows the OM and the ordinate axis the corresponding SA as well as the direction of the evaluation scores, where 10 means the optimum. The filled red dots represent the mean value of the SAs of each system variants and the black continuous line represents the fitted regression line based on the mean values. The effect size Cohen's f, Pearson's correlation coefficient r and the p-value of the SLR model are listed under each graph.

As mentioned in Section II-C, due to the limited number of data points, the robustness of the SLR models is further tested utilizing the method by [26]. The red circles above and under the red filled points in Figure 10 represent the upper and

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

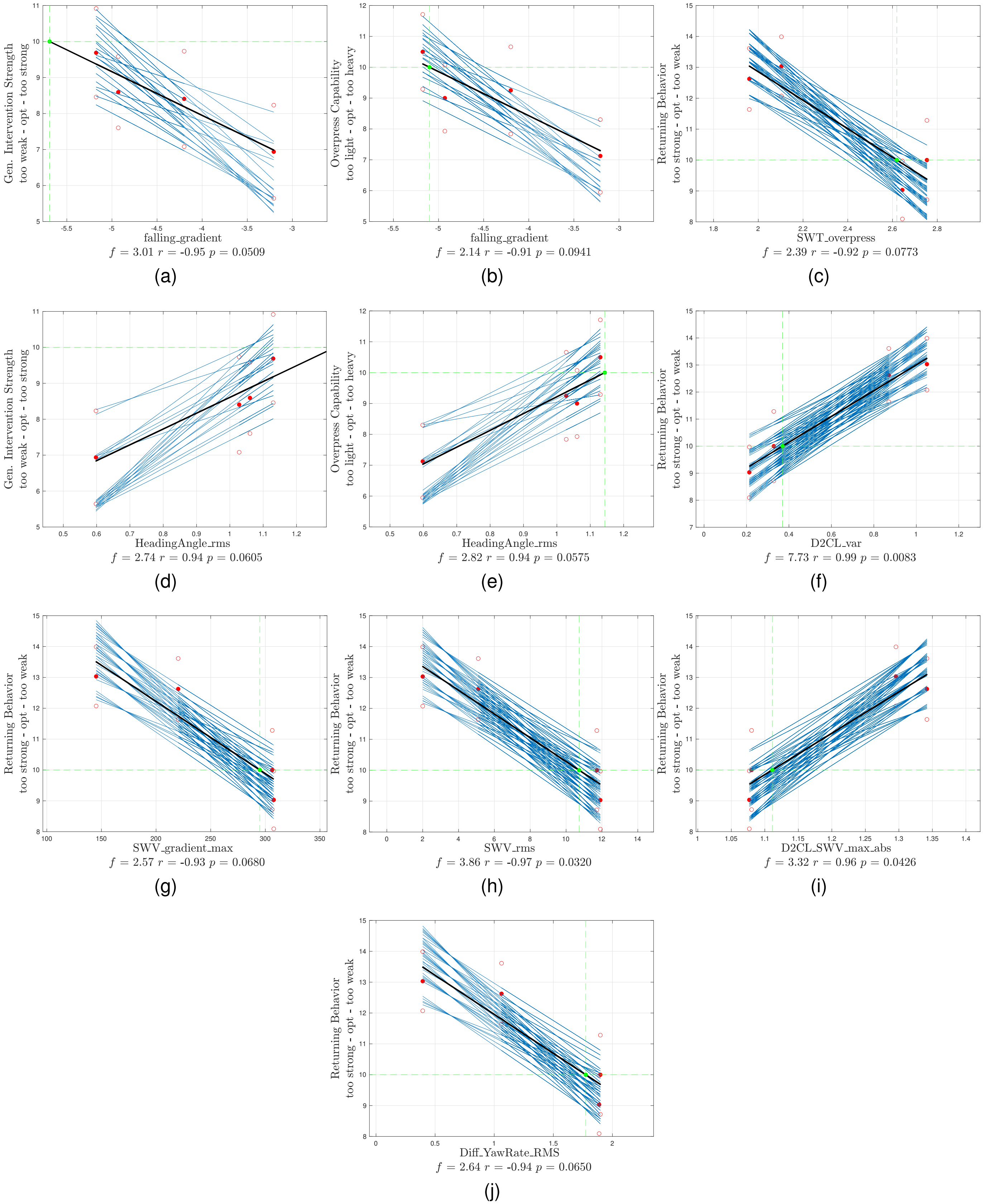


Fig. 10. Simple linear regression results for test maneuver Lane Change and Extended Curve Follow. (a) SA3-LC_OM11: General Intervention Strength - falling_gradient. (b) SA4-LC_OM11: Overpress Capability - falling_gradient. (c) SA10-LC_OM1: Returning Behavior - SWT_overpress. (d) SA3-ECF_OM21: General Intervention Strength - HeadingAngle_rms. (e) SA4-ECF_OM21: Overpress Capability - HeadingAngle_rms. (f) SA10-ECF_OM6: Returning Behavior - D2CL_var. (g) SA10-ECF_OM13: Returning Behavior - SWV_gradient_max. (h) SA10-ECF_OM14: Returning Behavior - SWV_rms. (i) SA10-ECF_OM15: Returning Behavior - D2CL_SWV_max_abs. (j) SA10-ECF_OM17: Returning Behavior - Diff_YawRate_rms.

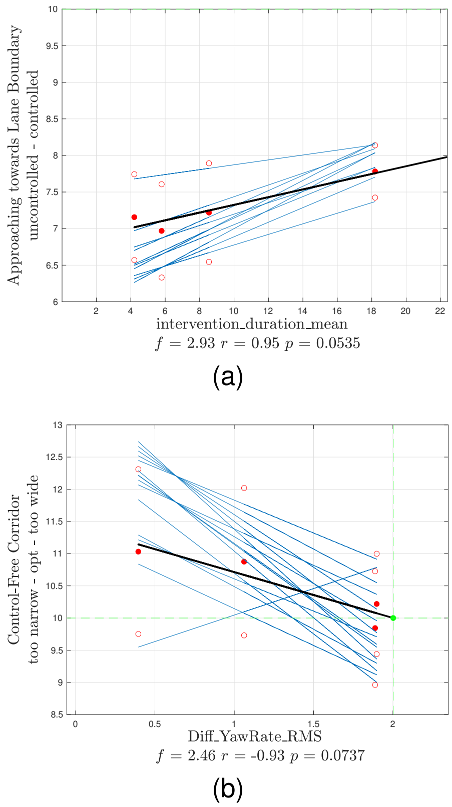


Fig. 11. Examples of non-robust simple linear regression results for test maneuver Extended Curve Follow. (a) Sparse regression lines. (b) Non-uniformed trends of the regression lines.

lower boundaries of the 90%-CI of the SA respectively. The blue lines are the regression lines based on all the possible combinations of the 3 characteristic values (upper boundary of 90%-CI, mean value, lower boundary of 90%-CI) of SAs with a p-value smaller than 0.1. The "regression-bundles" now could visualize the robustness of the SLR models found. The SLR model is not considered robust if the number of significant regressions is small (depicted in Figure 11a: 11 significant regression lines out of 81 possible ones) or the significant regression lines do not have a uniform trend, i.e. the correlation coefficient r of the regressions do not have the same sign (depicted in Figure 11b). These would mean that the SLR model does not necessarily hold within the 90%-CI of the SAs or the significance is not guaranteed.

The results shown in Figure 10 can therefore be all considered robust, as the regression-bundles are dense and the regression lines have a uniform trend with similar correlation coefficients (standard deviation of r smaller than 0.033). The linear regression models for Lane Change are as follows:

$$y_{SA3} = 3.09 - 1.21 \cdot x_{LC\_OM11}, \quad (5)$$
$$y_{SA4} = 2.72 - 1.43 \cdot x_{LC\_OM11}, \quad (6)$$
$$y_{SA10} = 22.08 - 4.61 \cdot x_{LC\_OM1}. \quad (7)$$

Eq. 5 and Eq. 6 show a negative correlation between the LC_OM11 *falling_gradient* and the SA3 General Intervention Strength and SA4 Overpress Capability respectively. This means the faster the steering wheel torque descends after

TABLE VIII
OPTIMAL VALUES OF THE OMS IDENTIFIED FROM THE SLR MODELS

	Subjektive Assessment	Objektive Metric	Optimal value
LC	Gen. Intervention Strength	Falling_gradient	-5.69 Nm/m
	Overpress Capability	Falling_gradient	-5.10 Nm/m
	Returning Behavior	SWT_overpress	2.62 Nm
ECF	Gen. Intervention Strength	HeadingAngle_rms	1.32 deg
	Overpress Capability	HeadingAngle_rms	1.14 deg
	Returning Behavior	D2CL_var	0.37 m^2
		SWV_gradient_max	294.93 deg/s^2
		SWV_RMS	10.73 deg/s
		D2CL_SWV_max	1.11 m
		Diff_YawRate_RMS	1.77 deg/s

pressing over the lane marking, the stronger the driver perceives the intervention strength and the heavier the overpress capability. Eq. 7 shows that a higher steering wheel torque at the lane marking correlates with a stronger returning behavior.

The optimal value of the OMs is identified by finding the intercept of SA = 10 (green dashed horizontal line) and the regression line (black solid line), marked with a green filled dot in Figure 10. The identified optimal values are listed in Table VIII.

2) Results of Extended Curve Follow Maneuver: The SA-OM combination matrix of the maneuver Extended Curve Follow in a similar manner of Table II is attached in Appendix C. After the ANOVA test of the OMs, 3 OMs are identified as unsuitable for characterizing the LDA system, which are ECF_OM4 *D2BL_mean*, ECF_OM20 *TLC_start_of_intervention_std*, ECF_OM22 *D2CL_HeadingAngle_max_abs*. 41 remaining potential SA-OM combinations are analyzed for their correlation. 7 strong correlations are found and are illustrated in Figure 10d - 10j. All of the correlations are robust within the 90%-CI. The equation of the linear regression models for Extended Curve Follow are listed as follows:

$$y_{SA3} = 4.21 + 4.40 \cdot x_{ECF\_OM21}, \quad (8)$$
$$y_{SA4} = 3.77 + 5.44 \cdot x_{ECF\_OM21}, \quad (9)$$
$$y_{SA10} = 8.23 + 4.77 \cdot x_{ECF\_OM6}, \quad (10)$$
$$y_{SA10} = 16.9 - 0.02 \cdot x_{ECF\_OM13}, \quad (11)$$
$$y_{SA10} = 14.12 - 0.38 \cdot x_{ECF\_OM14}, \quad (12)$$
$$y_{SA10} = -4.90 + 13.41 \cdot x_{ECF\_OM15}, \quad (13)$$
$$y_{SA10} = 14.48 - 2.53 \cdot x_{ECF\_OM17}. \quad (14)$$

SA3 General Intervention Strength and SA4 Overpress Capability show a positive correlation with ECF_OM21 *HeadingAngle_rms*. This means the more the heading angle of the vehicle oscillates when following a curve, the stronger the perceived intervention strength and the heavier it is, to override the function.

SA10 Returning Behavior shows a positive correlation with ECF_OM6 *D2CL_var* and ECF_OM15 *D2CL_SWV_max_abs*. The former correlation indicates that the more the D2CL varies from its mean, which could be caused by the less dominant position controller, the weaker and less agile the perceived returning behavior. The positive correlation SA10-ECF_OM15 indicates that the further away the vehicle is from the lane center at the point of time, where the steering wheel velocity reaches its maximum, the weaker and less agile the perceived returning behavior. This is because a larger value of ECF_OM15 *D2CL_SWV_max_abs* could mean a later and/or weaker intervention of LDA.

SA10 Returning Behavior shows a negative correlation with ECF_OM13 *SWV_gradient_max*, ECF_OM14 *SWV_rms* and ECF_OM17 *Diff_YawRate_rms*. The correlation SA10-ECF_OM13 indicates that the faster the steering wheel velocity increases/decreases, the stronger the perceived returning behavior. The correlation SA10-ECF_OM14 and SA10-ECF_OM17 means that a largely varying steering wheel velocity and a largely varying differential yaw rate indicates a strong perceived returning behavior.

The identified optimal values of the OMs are listed in Table VIII.

3) Results of Curve Follow Maneuver: According to the results of the ANOVA test for the OMs of Curve Follow, 11 OMs are significantly different between the system variants and are therefore potentially suitable for characterizing the LDA system. However, only 4 of the 19 SA-OM combinations show a weak linear correlation and the rest do not show any linear correlation at all. This could be caused by several reasons. One possible reason is that the maneuver Curve Follow is not suitable for characterizing the 4 LDA variants, since only one system intervention does not provoke enough variance in the system response of the 4 variants. Another possible reason could be that the potential correlations are not linear. However, the database with limited system observations is not robust enough to allow the inspection of the non-linear relationships.

IV. Discussion

The results of this study show that the maneuver Lane Change and Extended Curve Follow are suitable for the LDA characterization, whereas the maneuver Curve Follow is not. The reason for this could be that one single intervention in the curve did not produce sufficiently significant differences in the system response of the 4 variants. It is more pronounced in the case of an LDA system than in the case of an LKAS Type II system, as the system only intervenes close to the lane markings and the intervention is particularly short. On the other hand, the maneuver Extended Curve Follow allowed the system to intervene as many times as necessary/possible, provoking different system behaviors.

For the subjective characterization, it is important to find out whether the professional and the normal driver perceive the system attributes in a similar way. The results show that the professional drivers and the normal drivers use the rating scale differently. While the normal drivers tend to give more extreme scores, especially high scores (higher than 8), the professional drivers rarely do. This shows that professional drivers are better able to map the different system characteristics onto the rating scale. It confirms that the professional drivers have a more stable internal reference model due to more experience in test driving and a better understanding of the system in general. A score above 9 would indicate a near-perfect system under test, for which no improvement would be desirable.

TABLE IX
CATEGORIZATION OF SAs

SA Main Criteria	#	SA Sub-Criteria	Category
Driver Interaction	1	Co-Steering	preference
	2	Counter-Steering	preference
	3	General Intervention Strength	sensory
	4	Override Capability at Lane Boundary	sensory
	5	Harmony of Steering Wheel Movement	preference
Perceived Safety	6	Approaching towards Lane Boundary	sensory
	7	Maximum Lane Overshoot	sensory
	8	Reliability and Reproducibility	sensory
Functional Performance	9	Control-Free Corridor	sensory
	10	Returning Behavior	sensory
	11	Disengagement Position	sensory
	12	Disengagement Angle	sensory

This is rarely the case in vehicle development and professional drivers tend to be very cautious about it. However, the central tendencies and spreads of the two groups are not significantly different. This shows that the difference between professional and normal drivers is basically only in the use of the rating scale in the high score range. In addition to driver type, driver style also has a significant impact on subjective evaluation, while road type does not.

To go one step further, the authors try to answer which attributes these two driver groups evaluate consistently. The SAs can be divided into “sensory” and “preference” category as in Table IX. The “sensory” category means that the driver functions as a “sensor” and evaluates the perceived magnitude of the respective signals, e.g. high-low. Conversely, the “preference” category includes SAs that are based on the driver’s subjective preference, e.g. good-bad. According to the results, both groups can differentiate the 4 system variants in the aspects of 3 sub-criteria on both road types, namely SA3 General Intervention Strength, SA4 Override Capability at Lane Boundary (sub-criteria in the group of Driver Interaction) and SA10 Returning behavior (sub-criterion in the group of Functional Performance). First of all, these 3 sub-criteria belong to the “sensory” category of the SA. The “sensory” category SAs could be more straightforward for the subjects to evaluate, especially for the normal drivers with less experience, and might be less influenced by subjects’ individual differences. Secondly, these 3 sub-criteria are perceived mainly based on the steering wheel torque as well as movement, heading angle and the change of heading angle. A plausible reason for the consistent evaluation is that these signals can be perceived more dominantly and processed more accurately by the subjects on a static driving simulator.

Subjects from both groups could not consistently evaluate the sub-criteria from the category “preference”, namely SA1 Co-Steering, SA2 Counter-Steering or SA5 Harmony of Steering Wheel Movement. One reason for this result could be that the difference between the system variants does not outweigh the difference between the subjective opinions of the drivers. In addition, unlike the other criteria, there is no defined maneuver for the evaluation of Co-Steering and Counter-Steering, but it is left to the individual driver. This could have introduced more individual influences in the maneuver execution. Furthermore, the relatively short intervention time compared to an LKAS Type II, which aims to keep the vehicle near the center of the lane, makes the evaluation of these two

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

attributes more difficult.

The rest of the "sensory" sub-criteria SA6, SA7, SA8, SA9, SA11 and SA12 could not be consistently evaluated by both groups of drivers on both types of road, providing insufficient evidence to support the suitability of these sub-criteria in the test setup. The "sensory" criteria can all theoretically be "translated" into one or more objective parameters. SA7, SA9, SA11 and SA12 are rather straightforward and can be "translated" as follows: SA7 Maximum Lane Overshoot ∼ ECF_OM3 *D2BL_min*, SA9 Control-Free Corridor ∼ LC_OM6 *deadband_width*, SA11 Disengagement Position ∼ ECF_OM8 *final_pos_mean* and CF_OM5 *final_pos_by_sym*, SA12 Disengagement Angle ∼ ECF_OM24 *final_HeadingAngle_mean*. These OMs are all significantly different between the 4 system variants, indicating that these SAs should also be perceived differently from an objective point of view. The contradictory results indicate that the drivers could not subjectively perceive the objective difference. When an LDA intervention is completed and deactivated, the LDA system icon on the dashboard changes from green to gray without any audible or haptic indication. This could lead to an inaccurate estimation of the intervention end point, and thus the vehicle's position and heading angle at that time, if the LDA intervention fades out smoothly and the driver is not paying close attention. Note that SA7, SA9 and SA11 are highly dependent on the perception of the position of the ego vehicle in the lane. Therefore, the authors suggest that the drivers' distance estimation in the simulation animation may be inaccurate, which could be improved to some extent by intensive perspective tuning.

SA6 Approaching towards Lane Boundary and SA8 Reliability and Reproducibility have more corresponding OMs. The OMs for SA6 are from the maneuver Curve Follow and are mainly the characteristic values of each signal in the approaching process, e.g. CF_OM12 *SWV_gradient_max_approach* and CF_OM22 *Diff_YawRate_max_abs_approach*. The OMs for SA8 are mainly standard deviation of each signal in the maneuver Extended Curve Follow, e.g. ECF_OM9 *intervention_pos_std* and ECF_OM20 *TLC_start_of_intervention_std*. The majority of these OMs are not significantly different between the 4 system variants, it could be assumed that the difference between the variants are not great enough to be subjectively perceived in the first place. It is therefore not necessary to further discuss whether SA6 and SA8 are suitable for the characterization.

In the next step, this paper further analyzed the relationship between the objective and subjective evaluation of the LDA variants, attempting to explain driver's subjective assessment with OM. This examined the potential of predicting driver's subjective evaluation of the system using merely objective metrics in future research. First of all, it is investigated which objective metrics are relevant for driver's subjective perception on a static driving simulator. Considering the found strong correlations between SA and OM, it can be concluded that the most important parameters are characteristic values of the steering wheel torque and steering wheel movement, e.g. steering wheel velocity, steering wheel velocity gradient. However, the absolute values of the ego vehicle position and of the heading angle at characteristic time point, e.g. at intervention start, intervention end, or at the furthest point from lane center, do not show strong linear correlation or any linear correlation with the SAs. The only two from category D2L and Heading Angle that have a strong correlation with SAs are ECF_OM6 *D2CL_var* and ECF_OM21 *HeadingAngle_rms*. This indicates that the changing rate of the ego position and heading angle are more relevant for the subjective evaluation than the absolute value on a static driving simulator.

SA3 General Intervention Strength and SA4 Override Capability at Lane Boundary can be described by *Falling_gradient* from Lane Change and *HeadingAngle_rms* from Extended Curve Follow. This means that the faster the steering wheel torque drops, and the more the heading angle varies around the mean value, the stronger the subjects perceive the general intervention strength and the more difficult it is to override the system. However, SA3 and SA4 do not show a strong enough linear correlation with steering wheel torque directly. On the other hand, a higher steering wheel torque (LC_OM1, LC_OM2, LC_OM3) is a strong indicator for a stronger returning behavior (SA10). SA10 Returning Behavior also show a strong linear correlation with the OMs related with steering wheel velocity and the spread of the steering wheel velocity as well as the spread of ego vehicle position and heading angle. The optimal value of the 8 OMs *Falling_gradient*, *SWT_overpress*, *HeadingAngle_rms*, *D2CL_var*, *SWV_gradient_max*, *SWV_rms*, *D2CL_SWV_max* and *Diff_YawRate_rms* are identified. For an optimal intervention strength (SA3), the 4 variants in this study are all too weak.

As for the main criteria, it is found out that only professional drivers can differentiate the 4 system variants in these aspects on highway, namely SA-I Driver Interaction, SA-II Perceived Safety and SA-III Functional Performance. In order to gain an insight into which OMs are relevant to the subjective perception of these main criteria, SLR is also carried out in the same way as for the sub-criteria, although the SAs for the main criteria are not consistent for both drivers and both road types. The found strong correlations are attached in Appendix D.

V. Conclusions and Outlook

The results of this paper indicate that, despite limited motion cues, a static driving simulator is generally suitable for characterizing an LDA system, since the Operational Design Domain (ODD) of the system is mostly in the low dynamic range. However, the following aspects should be taken into consideration. i) It is recommended to use professional drivers or engineers from related fields as test drivers for LDA evaluation. This is because they can map the range of system characteristics onto the rating scale more consistently than normal drivers. In this way the variance of personal experience and preferences can be eliminated as far as possible, resulting in a more stable quality of subjective assesment. ii) The SAs of the sub-criteria should be from the "sensory" instead of the "preference" category to reduce interpersonal differences and focus on the system differences. Especially when the sample size of subjects is small, it is recommended to focus on the robust SA criteria. As for the main criteria, Driver Interaction, Perceived Safety and Functional Performance, are anticipated to exhibit nonlinear multivariate relationships with the OMs. While this paper provides initial insights into the relevant OMs that influence these SAs using SLR, further exploration requires a larger database with more system variants for robust model training and testing. iii) The focus of the objective characterization and objectivization should be laid on the main information channels, i.e. steering wheel movement and driver's interaction with it, as well as the ego vehicle change of position and heading angle.

Further research will focus on optimizing the LDA characterization process on a static driving simulator based on the findings of this study. Expanding the database to include a broader range of system variants will allow the transferability of the results to be tested. Concurrently, it will enable more complex algorithms for modeling potential nonlinear MIMO relationships between SAs and OMs. Additionally, future investigations will focus on the validation of the subjective evaluation on the simulator by comparing the results from other domains such as road tests.

Acknowledgments

The authors acknowledge TU Wien Bibliothek for financial support through its Open Access Funding Programme.

References

[1] H. Winner, S. Hakuli, F. Lotz, and C. Singer, Eds., *Handbook of Driver Assistance Systems*. Cham: Springer International Publishing, 2016. [Online]. Available: http://link.springer.com/10.1007/978-3-319-12352-3

[2] E. Shi, T. M. Gasser, A. Seeck, and R. Auerswald, "The Principles of Operation Framework: A Comprehensive Classification Concept for Automated Driving Functions," *SAE International Journal of Connected and Automated Vehicles*, vol. 3, no. 1, pp. 12–03–01–0003, Feb. 2020. [Online]. Available: https://www.sae.org/content/12-03-01-0003/

[3] S. Wei, P. E. Pfeffer, and J. Edelmann, "State of the Art: Ongoing Research in Assessment Methods for Lane Keeping Assistance Systems," *IEEE Transactions on Intelligent Vehicles*, pp. 1–28, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10106476/

[4] M. Fritzsche, "Ein Beitrag zur Objektivierung des Sicherheitsempfindens mit Fahrermodellen bei Lenkstörungen," Dissertation, Universität Duisburg-Essen, Feb. 2016.

[5] E. Blana, "A Survey of Driving Research Simulators Around the World." Working Paper 481, Institute of Transport Studies, University of Leeds, 1996.

[6] T. Tüschen, *Konzeptionierung eines hochimmersiven und selbstfahrenden Fahrsimulators*, 1st ed., ser. Schriftenreihe des Lehrstuhls Kraftfahrzeugtechnik. Göttingen: Cuvillier Verlag, 2018, no. Band 9.

[7] M. E. W. Wiedemann, *Validierung der Fahrsimulation für das Erleben und Beurteilen fahrdynamischer Eigenschaften*, 1st ed., ser. Audi-Dissertationsreihe. Göttingen: Cuvillier Verlag, 2016, no. Band 113.

[8] U. Eryilmaz, H. Sancar Tokmak, K. Cagiltay, V. Isler, and N. O. Eryilmaz, "A novel classification method for driving simulators based on existing flight simulator classification standards," *Transportation Research Part C: Emerging Technologies*, vol. 42, pp. 132–146, May 2014. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0968090X14000539

[9] H. Winner and C. Zöller, "Fahrsimulatorkonzepte im Wandel," in *2019 Darmstädter Kolloquium - Hands off, Human Factors off? Welche Rolle spielen Human Factors in der Fahrzeugautomation?*, Technische Universität Darmstadt, Feb. 2019. [Online]. Available: https://tuprints.ulb.tu-darmstadt.de/id/eprint/8067

[10] F. Hartwich, C. Hollander, D. Johannmeyer, and J. F. Krems, "Improving Passenger Experience and Trust in Automated Vehicles Through User-Adaptive HMIs: "The More the Better" Does Not Apply to Everyone," *Frontiers in Human Dynamics*, vol. 3, p. 669030, Jun. 2021. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fhumd.2021.669030/full

[11] H. Zheng, L. Luo, and L. Wang, "Research on Steering Performance of Steer-By- Wire Vehicle," Apr. 2018, pp. 2018–01–0823. [Online]. Available: https://www.sae.org/content/2018-01-0823/

[12] W. Wang, J. Xi, C. Liu, and X. Li, "Human-Centered Feed-Forward Control of a Vehicle Steering System Based on a Driver's Path-Following Characteristics," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–14, 2016. [Online]. Available: http://ieeexplore.ieee.org/document/7576705/

[13] M. Mulder, D. A. Abbink, and E. R. Boer, "Sharing Control With Haptics: Seamless Driver Support From Manual to Automatic Control," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 54, no. 5, pp. 786–798, Oct. 2012. [Online]. Available: http://journals.sagepub.com/doi/10.1177/0018720812443984

[14] Z. Huang, Y. Wu, and J. Liu, "Research on effects of pattern, amplitude and frequency of pulse steering torque warnings for lane departure," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 31, pp. 67–76, May 2015. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1369847815000480

[15] Z. Wang, R. Zheng, T. Kaizuka, and K. Nakano, "Relationship Between Gaze Behavior and Steering Performance for Driver–Automation Shared Control: A Driving Simulator Study," *IEEE Transactions on Intelligent Vehicles*, vol. 4, no. 1, pp. 154–166, Mar. 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8574934/

[16] Z. Wang, X. Liao, C. Wang, D. Oswald, G. Wu, K. Boriboonsomsin, M. J. Barth, K. Han, B. Kim, and P. Tiwari, "Driver Behavior Modeling Using Game Engine and Real Vehicle: A Learning-Based Approach," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 738–749, Dec. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9084240/

[17] X. Zhou, H. Jiang, A. Li, and S. Ma, "A New Single Point Preview-Based Human-Like Driver Model on Urban Curved Roads," *IEEE Access*, vol. 8, pp. 107 452–107 464, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9113240/

[18] R. Tang and Z. Jiang, "Driver's Perception Model in Driving Assist," in *2020 IEEE 20th International Conference on Software Quality, Reliability and Security Companion (QRS-C)*. Macau, China: IEEE, Dec. 2020, pp. 237–240. [Online]. Available: https://ieeexplore.ieee.org/document/9282702/

[19] S. Scherer, A. Dettmann, F. Hartwich, T. Pech, A. C. Bullinger, and G. Wanielik, "How the driver wants to be driven - Modelling driving styles in highly automated driving," Munich, Nov. 2015.

[20] H. Bellem, B. Thiel, M. Schrauf, and J. F. Krems, "Comfort in automated driving: An analysis of preferences for different automated driving styles and their dependence on personality traits," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 55, pp. 90–100, May 2018. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1369847817301535

[21] M. Jentsch and A. C. Bullinger, "Is simulation (not) enough? Results of a validation study of an autonomous emergency braking system on a test track and in a static driving simulator," in *Proceedings of the Human Factors and Ergonomics Society Europe Chapter 2014 Annual Conference*. Lisbon, Portugal: HFES, 2014, pp. 161–174.

[22] F. W. Siebert, M. Oehl, and H.-R. Pfister, "The influence of time headway on subjective driver states in adaptive cruise control," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 25, pp. 65–73, Jul. 2014. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1369847814000710

[23] T. Denoual, J.-F. Petiot, F. Mars, and A. Kemeny, "Predicting the Subjective Evaluation of Drivers in a Driving Simulator During Loss of Adherence," in *Volume 2: Applied Fluid Mechanics; Electromechanical Systems and Mechatronics; Advanced Energy Systems; Thermal Engineering; Human Factors and Cognitive Engineering*. Nantes, France: American Society of Mechanical Engineers, Jul. 2012, pp. 773–780. [Online]. Available: https://asmedigitalcollection.asme.org/ESDA/proceedings/ESDA2012/44854/773/230710

[24] M. Becker, D. Lee, K. Kim, M. Melchior, M. Niegl, and P. E. Pfeffer, "Transition Steering Feel of Handover and Takeover Scenarios Between Human and Automated Steering," in *Proceedings of the FISITA - Technology and Mobility Conference Europe 2023*. Barcelona, Spain: FISITA, 2023. [Online]. Available: https://www.fisita.com/library/fwc2023-sca-050

[25] J. Cohen, *Statistical power analysis for the behavioral sciences*, 2nd ed. New York, NY: Psychology Press, 2009.
[26] M. Harrer, "Characterisation of Steering Feel," Dissertation, University of Bath, Mar. 2007.
[27] H. J. Wolf, "Ergonomische Untersuchung des Lenkgefühls an Personenkraftwagen," Ph.D. dissertation, Technische Universität München, Mar. 2009.
[28] A. Fen, "Simulative Ermittlung von Key-Performance-Indikatoren komfortorientierter Fahrerassistenzsysteme," *ATZ - Automobiltechnische Zeitschrift*, vol. 1/2018, pp. 96–99.

Sijie Wei received the B.S. degree in automotive engineering from Tongji University, Shanghai, China, in 2014. She received the M.S. degree in automotive mechatronics from Munich University of Applied Sciences, Germany, in 2017. She is currently Ph.D. student at TU Wien. Her research field is vehicle dynamics and human-centered development of Advanced Driver Assistance Systems.

Matthias Becker completed his B.S. degree in physical engineering at Munich University of Applied Sciences in 2014. He then completed his M.S. degree in automotive mechatronics, also at MUAS, until 2015. He currently works as a research assistant at MUAS in the Automotive Engineering Laboratory under the direction of Prof. Dr. Peter E. Pfeffer and as a project manager at MdynamiX, the affiliated institute of MUAS. His research areas include the characterization, modeling and simulation of automated vehicle lateral guidance systems, in particular the interaction with humans during the steering process. The simulation of steering feel using steering wheel torque actuators and the generation of authentic steering feel for steer-by-wire systems are further key areas of research.

Peter E. Pfeffer received the B.S. and the M.S. degree from TU Wien, Austria. From 2002 to 2007 he was lecturer at the Mechanical Engineering Department of the University of Bath, where he researched the interaction of vehicle and steering system regarding handling and received his Ph.D. degree in 2007. He is currently a Professor of automotive engineering at the Munich University of Applied Sciences, Germany, since 2007 and is cofounder and CEO of MdynamiX AG since 2014. He is the Scientific Director of the International Munich Chassis Symposium and editor of the Steering Handbook (Springer Cham, 2017). He is a member of the scientific board of the VDI (the Association of German Engineers) and is leading the regional section South Bavaria. His research interests are automated driving, vehicle dynamics, steering systems, steering feel, elastomer and hydro mounts.

Johannes Edelmann received the Ph.D. degree in 2008 and his venia docendi for Technical Dynamics in 2011 at TU Wien, Austria . From 2018 to 2022 he was an Associated Professor at the Institute of Mechanics and Mechatronics, TU Wien. Since October 2021 he is a Professor for Technical Dynamics at the Institute of Mechanics and Mechatronics. His research interests are applied multi-body dynamics, stability of dynamical systems, vehicle dynamics, driver modeling, dynamic behavior of bicycles, scooters, motorcycles, and automobiles, development of driver assistance systems and vehicle dynamics control systems.

APPENDIX A
DISTRIBUTION OF SAS

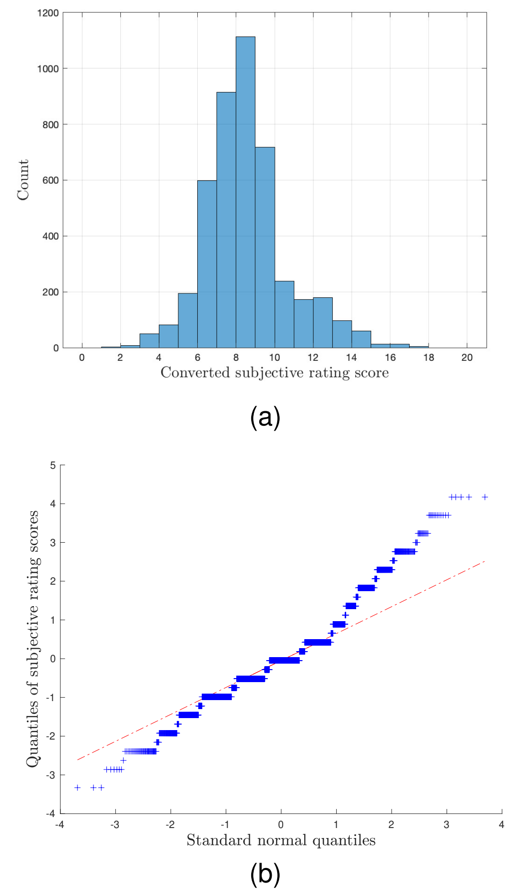


Fig. 12. Distribution of all subjective assessments. (a) Histogram of SA. (b) QQ-plot of SA.

APPENDIX B
LISTS OF RELEVANT OBJECTIVE METRICS FOR RESPECTIVE TEST MANEUVERS

Test Maneuver: Extended Curve Follow

D2L: This category focuses on the characteristic values of the ego vehicle's relative position within the ego lane.		
ECF_OM1	*D2LL_min* [m]	Minimal distance from the outer edge of the front left tire to the left lane marking during the whole measurement. The measurement begins when the vehicle enters the curve and ends when the vehicle fails to stay in its ego lane or the curve ends.
ECF_OM2	*D2RL_min* [m]	Minimal distance from the outer edge of the front right tire to the right lane marking during the whole measurement.
ECF_OM3	*D2BL_min* [m]	Minimal distance of the ego vehicle to the boundary line (D2BL) during the whole measurement. D2BL is defined as the smaller of D2LL and D2RL.
ECF_OM5	*D2BL_std* [m]	Standard deviation of the distance of the ego vehicle to the boundary line (D2BL) during the whole measurement.
ECF_OM6	*D2CL_var* [m]	Variance of the distance of the ego vehicle to the lane center (D2CL) during the whole measurement.
ECF_OM7	*intervention_pos_mean* [m]	Mean value of D2CL when the LDA system starts the intervention of all the interventions during the whole measurement.
ECF_OM8	*final_pos_mean* [m]	Mean value of D2CL when the LDA system ends the intervention of all the interventions during the whole measurement.
ECF_OM9	*intervention_pos_std* [m]	Standard deviation of D2CL when the LDA system starts the intervention of all the interventions during the whole measurement.
ECF_OM10	*final_pos_std* [m]	Standard deviation of D2CL when the LDA system ends the intervention of all the interventions during the whole measurement.
Time: This category focuses on the length of characteristic time periods.		
ECF_OM11	*intervention_duration* [s]	Mean value of the duration of all the interventions during the whole measurement.
ECF_OM12	*intervention_duration_per* [%]	Ratio of the intervention duration to the total length of the measurement in percentage.
SWV Gradient: This category focuses on the characteristic values of steering wheel velocity gradient. SWV gradient is defined as the time derivative of the steering wheel velocity.		
ECF_OM13	*SWV_gradient_max* [deg/s^2]	Maximal steering wheel velocity gradient during the whole measurement.
SWV: This category focuses on the characteristic values of steering wheel velocity.		
ECF_OM14	*SWV_RMS* [deg/s]	Root mean square of steering wheel velocity during the whole measurement.
ECF_OM15	*D2CL_SWV_max* [m]	D2CL at the point of time when steering wheel velocity reaches its absolute maximum value of the whole measurement.
Differential Yaw Rate: This category focuses on the characteristic values of differential yaw rate. Differential yaw rate is defined as the difference between the actual measured yaw rate and the theoretical yaw rate for the stationary circular maneuver for a given curve radius and vehicle velocity. The definition equation is $\psi_{diff} = \psi - \frac{v}{R}$ with ψ represents the actual yaw rate, v the constant vehicle velocity and R the curve radius.		
ECF_OM16	*Diff_YawRate_max_abs* [deg/s]	Maximal absolute value of differential yaw rate during the whole measurement.
ECF_OM17	*Diff_YawRate_RMS* [deg/s]	Root mean square of differential yaw rate during the whole measurement.
ECF_OM18	*D2CL_Diff_YawRate_max* [m]	D2CL at the point of time when differential yaw rate reaches its absolute maximum value of the whole measurement.
TLC: This category focuses on the values of Time to Line Crossing at characteristic time points. Time to Line Crossing (TLC) is defined as the time remaining before the vehicle crosses the lane marking, calculated using the current vehicle velocity and heading angle. It is defined by the following equation: $TLC = \frac{d}{v \cdot \sin\theta}$ with d indicating the distance from the lane marking to the outer corner of the front tire, whichever is closer to the lane marking, v the vehicle velocity and θ the heading angle.		
ECF_OM19	*TLC_start_of_intervention* [s]	Mean value of TLC at the start of each intervention during the whole measurement.
Heading Angle: This category focuses on the characteristic values of heading angle of the ego vehicle. The heading angle is defined as the angle between the tangent to the lane marking at the projection of the Center of Gravity (CoG) of the ego vehicle onto the lane marking and the positive direction of the y-axis in the vehicle's coordinate system.		
ECF_OM21	*HeadingAngle_rms* [deg]	Root mean square of the heading angle of the ego vehicle during the whole measurement.
ECF_OM23	*intervention_HeadingAngle_mean* [deg]	Mean value of the heading angle at the start of each intervention during the whole measurement.
ECF_OM24	*final_HeadingAngle_mean* [deg]	Mean value of the heading angle at the end of each intervention during the whole measurement.
ECF_OM25	*intervention_HeadingAngle_std* [deg]	Standard deviation of the heading angle at the start of each intervention during the whole measurement.
ECF_OM26	*final_HeadingAngle_std* [deg]	Standard deviation of the heading angle at the end of each intervention during the whole measurement.

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

Test Maneuver: Curve Follow

D2L: This category focuses on the characteristic values of the ego vehicle's relative position within the ego lane.		
CF_OM1	*D2BLi_min* [m]	Minimal value of the distance of the front tire, whichever is on the inner side of the curve, to the inner lane marking of the curve during the first
CF_OM4	*intervention_pos_by_sym* [m]	D2CL at the point of time when the first intervention starts, indicated by the symbol on speedometer.
CF_OM5	*final_pos_by_sym* [m]	D2CL at the point of time when the first intervention ends, indicated by the symbol on speedometer.
CF_OM6	*D2BL_mean* [m]	Mean value of the distance of the ego vehicle to boundary line during the first intervention.
CF_OM7	*D2BL_std* [m]	Standard deviation of the distance of the ego vehicle to boundary line during the first intervention.
Time: This category focuses on the length of characteristic time periods.		
CF_OM8	*intervention_duration* [s]	Duration of the LDA intervention.
CF_OM9	*intervention_duration_approach* [s]	Duration of the LDA intervention when approaching the lane marking, i.e. time from the start of the LDA intervention to the time when the ego vehicle reaches the furthest point from the ego lane center (maximum D2CL).
CF_OM10	*intervention_duration_return* [s]	Duration of the LDA intervention when returning from the lane marking, i.e. time from when the ego vehicle starts to return from the furthest point from the ego lane center (maximum D2CL) to the end of the LDA intervention.
Differential Yaw Rate: This category focuses on the characteristic values of differential yaw rate.		
CF_OM21	*Diff_YawRate_RMS* [deg/s]	Root mean square of differential yaw rate during the LDA intervention.
Heading Angle: This category focuses on the characteristic values of heading angle of the ego vehicle.		
CF_OM26	*HeadingAngle_abs_max* [deg]	Maximal absolute value of the heading angle of the ego vehicle during the LDA intervention.
CF_OM28	*HeadingAngle_max_return* [deg]	Maximal absolute value of the heading angle of the ego vehicle during the returning process of the LDA intervention.

APPENDIX C
SA-OM COMBINATION MATRIX OF TEST MANEUVER EXTENDED CURVE FOLLOW AND CURVE FOLLOW

					SA		
					3	4	10
					General Intervention Strength	Override Capability at Lane Boundary	Returning Behavior
OM	ECF	D2L	1	D2LL_min	1	1	1
			2	D2RL_min	1	1	1
			3	D2BL_min	1	1	1
			5	D2BL_std			
			6	D2CL_var	1	1	1
			7	intervention_pos_mean			
			8	final_pos_mean			1
			9	intervention_pos_std			
			10	final_pos_std			
		Time	11	intervention_duration	1		1
			12	intervention_duration_per	1	1	1
		SWV gradient	13	SWV_gradient_max	1	1	1
		SWV	14	SWV_RMS	1	1	1
			15	D2CL_SWV_max	1	1	1
		DiffYawRate	16	Diff_YawRate_max_abs	1		1
			17	Diff_YawRate_RMS	1	1	1
			18	D2CL_Diff_YawRate_max	1	1	1
		TLC	19	TLC_start_of_intervention			
		HeadingAngle	21	HeadingAngle_rms	1	1	1
			23	intervention_HeadingAngle_mean	1	1	
			24	final_HeadingAngle_mean			1
			25	intervention_HeadingAngle_std			
			26	final_HeadingAngle_std			
	CF	D2L	1	D2BLi_min	1	1	1
			4	intervention_pos_by_sym			
			5	final_pos_by_sym			1
			6	D2BL_mean	1	1	1
			7	D2BL_std			
		Time	8	intervention_duration	1		1
			9	intervention_duration_approach	1	1	
			10	intervention_duration_return	1	1	1
		DiffYawRate	21	Diff_YawRate_RMS			
		Heading Angle	26	HeadingAngle_abs_max	1	1	
			28	HeadingAngle_max_return	1	1	1

This article has been accepted for publication in IEEE Transactions on Intelligent Vehicles. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TIV.2024.3433369

APPENDIX D
SLR RESULTS OF SA MAIN CRITERIA AND OM

SA main criteria	OM	SLR function
Driver Interaction	LC_mean_intervention_trq	$y = 5.77 + 0.44 \cdot x$
	ECF_D2CL_var	$y = 7.87 - 0.92 \cdot x$
	ECF_intervention_duration_mean	$y = 6.74 + 0.06 \cdot x$
	ECF_final_pos_std	$y = 8.34 - 1.33 \cdot x$
	ECF_D2CL_SWV_max_abs	$y = 10.47 - 2.64 \cdot x$
Perceived Safety	LC_mean_intervention_trq	$y = 4.06 + 0.84 \cdot x$
	LC_Falling_gradient	$y = 3.79 - 0.74 \cdot x$
	ECF_ SWV_rms	$y = 5.95 + 0.14 \cdot x$
	ECF_final_pos_std	$y = 9.06 - 2.59 \cdot x$
	ECF_SWV_gradient_max	$y = 4.87 + 0.01 \cdot x$
	ECF_Diff_YawRate_rms	$y = 5.79 + 0.95 \cdot x$
	ECF_D2CL_var	$y = 8.10 - 1.74 \cdot x$
	ECF_intervention_duration_per	$y = 1.14 + 6.83 \cdot x$
Functional Performance	LC_mean_intervention_trq	$y = 4.91 + 0.65 \cdot x$
	LC_Falling_gradient	$y = 4.65 - 0.59 \cdot x$
	ECF_TLC_start_of_intervention_std	$y = 5.49 + 0.85 \cdot x$
	ECF_SWV_rms	$y = 6.37 + 0.11 \cdot x$
	ECF_SWV_gradient_max	$y = 5.52 + 0.01 \cdot x$
	ECF_Diff_YawRate_rms	$y = 6.24 + 0.74 \cdot x$
	ECF_D2BL_std	$y = 9.69 - 4.80 \cdot x$
	ECF_D2CL_var	$y = 8.03 - 1.34 \cdot x$
	ECF_intervention_duration_per	$y = 2.64 + 5.30 \cdot x$
	ECF_final_pos_std	$y = 8.75 - 1.96 \cdot x$