



## User Studies by Driving Simulators in the Era of Automated Vehicle

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**Abstract.** In order to increase safety in the road and improve the user experience in the vehicle, the user studies have been conducted by researchers and practitioners in the automobile industry over the decades. Also, over time, the technology and design inside the car have changed and are leading to a faster, safer, and more comfortable user experience in driving, thanks to the results gained from the user studies. On the other side, the boosting automated driving technology gives new challenges to user studies in the validation of new technologies from the user's perspective, improving the acceptance, employing the right usage, and so on. Laboratory driving simulation becomes one of the main methods for user studies because of its safety, ease of control, and precision in the scene restoration. In this paper, a typical fixed-base driving simulator will be introduced with a user interaction model in order to help the researchers to define the user study scope in each vehicle automation level and even predict the potential user study issues in the future autonomous vehicle technology and scenario. The strategy in the current study is to treat the different levels of automation in vehicles differently. Three case studies are provided accordingly from the low-automated to semi-autonomous driving and eventually fully autonomous driving. Each one addresses some of the critical points that should be paid attention to, in the user studies of the corresponding automation level, applying the previous model. In the low automation condition, the case study showed the effectiveness of the proposed method in the verification of olfactory modality interaction in the driver's attention maintenance. The case study in the semi-automation condition demonstrated the capacity of the current method of capturing the user's behavior changes in the take-over task, which is the most critical scenario in conditional autonomous driving. And the last case study showed the possibility to conduct comfort-related user studies in the full automation condition using the method, by monitoring the cognitive workload of users under different autonomous driving styles.

**Keywords:** User studies, Driving simulator, Driving simulation, User behavior studies, User experience.

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## 1 INTRODUCTION

Automation is changing the behavior of humans[20]. In particular, automated vehicles (AVs), which will be among the first automation systems rolled out to a broad public, will challenge learned communication patterns between different road participants[55]. User studies become crucial as a method that reveals the new communication patterns, inspires novel development of user interface (UI) and builds up new human-machine interaction (HMI)[10]. In general, the apparatus of user studies are three types: computational model, driving simulator, and real cars. The computer simulation is seldomly used because that it is only good at simulating certain behaviors such as the lane-changing movement and acceleration behaviors[49], and pedal control operations[2], but the human users' behavior are generally more unpredictable. The realistic level is the highest by using a real car in the testing field, both from the physical and the psychological aspects, but it is limited to treat only the existing technologies and designs. Another fact is that the current state of maturity of automated vehicles cannot cover all capabilities of automation. Laboratory driving simulation through the driving simulator is the most balanced choice. With the real user and the virtual driving scenario, it enables more freedom on the construction of the testing environment[24, 52]. Also very importantly, the compatibility of the results gained from the driving simulator and the real car have been verified in [40, 41, 53]. AVs have diverse automation taxonomies, defined by different associations or organizations, such as the National Highway Traffic and Safety Administration (NHTSA), and the Society of Automotive Engineers (SAE). Both of them listed the automation levels from no-automation (manually driving) to full automation (AVs system driving), but NHTSA divided it into 5 levels: from Level 0 to Level 4[34], while SAE divided it into 6 levels: from Level 0 to Level 5[42].

The driving simulator has been widely used in the user's behavior studies for all three levels of automation. For the Low automation level, eliminating human errors are essential to improve road safety. In the investigations into driver's speed choice and the lateral placement of their vehicles under the influence of roadside infrastructure[52]. Not only because of the driving scenario is replicable in the driving simulator, but also the possibility of recording the data in real-time along the testing session would be very helpful for the data processing. Another example relevant to the road safety issue is a study focusing on the emotional, cognitive, and sensorimotor stressors caused distracting of the driver[47], with experiments conducted in a driving simulator because the protocol per se contains dangerous elements that would place the participants in a fatal accident if being done in-road. In order to help human driver to enhance their operational safety, driver's assistance systems are also tested in driving simulators, for instance the Adaptive Cruise Control (ACC) feature [45] and Advanced Driving Assistance Systems (ADAS) [7]. For the Semi automation level, the user's studies focus on the transition of the control. By employing the driving simulator, the time needed for the human manual control recovery could be measured [16], and the usefulness and satisfaction of the Take-over request (TOR) could be investigated [4]. In the Full automation level, human users are no longer related to the driving tasks, their trust towards the AVs becomes the current focus[12, 19, 32].

In this paper, a model based on the relationship between the user and AVs will be proposed, aiming to get a comprehensive and structural understanding of the user studies issues at each level of automation, and potentially will be helpful to indicate the possible focuses in the further full automation driving scenario. Three case studies at the three categories of automation as mentioned before will be introduced to verify the usability of this model.

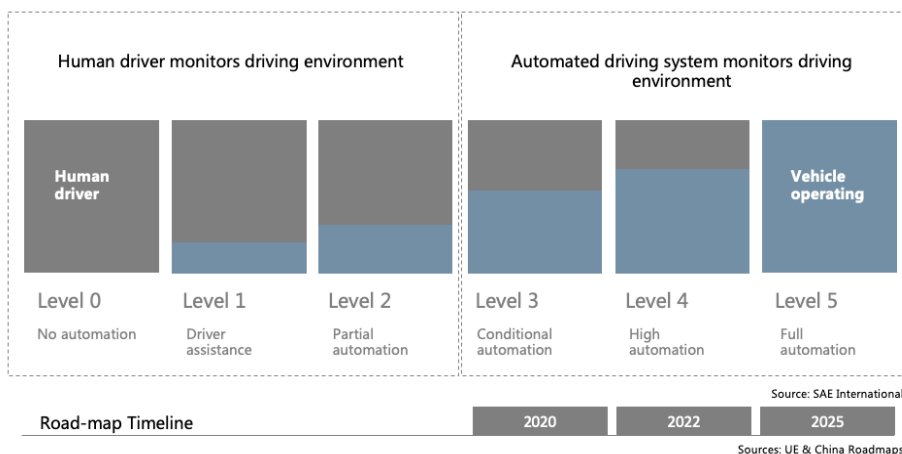
## 2 USER STUDY MODEL IN AUTOMATED DRIVING ERA

NHTSA defined vehicle's automation level from 0 to 4: No automation (Level 0), Function-specific automation (Level 1), Combined function automation (Level 2), Limited self-driving automation (Level 3), Full self-driving automation (Level 4). Similarly, also the automation levels by SAE goes from no-automation to full automation, but from level 0 to level 5, as shown in Figure 1. For both

sets of automation definitions, the trend of the human's role is extremely similar, from controlling everything to being merely the passenger. The automation levels by SAE International is developed from the levels of NHTSA, by splitting the Full self-driving automation into High Automation (Level 4) and Full automation (Level 5). Hence, in this paper the SAE International automation levels are taken as reference. Actually, from the user studies perspective of view, the automation levels in AVs could be divided into three categories:

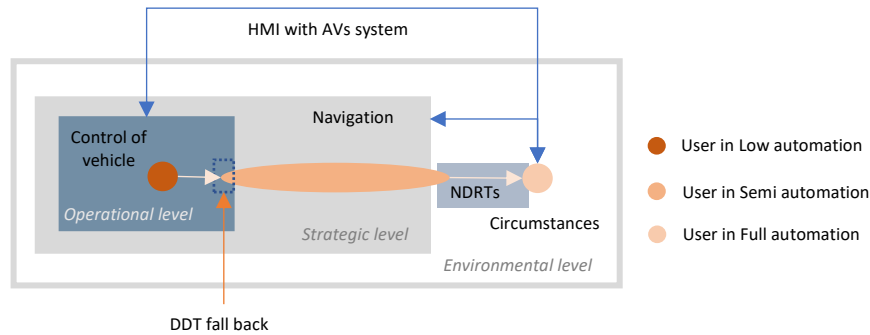
- Low automation (Level 0- Level 1): human driver holds the control;
- Semi automation (Level 2- Level 3): the control shifts between human user and the AVs system;
- Full automation (Level 4- Level 5): the AVs system controls the vehicle movement.

As shown in Figure 1, in each level, the Dynamic Driving Task (DDT) is completed by both the human driver and the vehicle operating, only the proportion of each agent changes. From Level 0 to Level 2, the main DDT falls to the human driver, in other words, the human driver needs to monitor the driving environment, while in the high levels of automation (Level 3- Level 5), the main roles of the human driver and the automated driving system exchanges. From the viewpoint of the complexity of the driving simulator, Level 2 and Level 3 (partial/conditional automation) should be paid more attention because human drivers are expected to reengage cognitively and physically in the driving task when the automated driving system fails. The DDT falling back to users in the transition from automated to manual driving should be treated carefully in the user studies.



**Figure 1:** The allocations of DDT in levels of automation in driving, adapt from SAE International report.

The human driver occupies less space in DDT along with the increase of automation level in Figure 1. Converting into another expression, the human driver is moving away from the control of the vehicle, as shown in Figure 2. The three positions of the user represent the position of attention resource of user in three categories, which also indicate the relationship between the user and the control of the vehicle, the navigation, and the driving circumstances, from three functional levels: operational level, strategic level, and environmental level. The first two levels are connected to the vehicle, and the third one is independent from the vehicle. Inside the Circumstances, there is a gray box, which represents the Non-driving-related tasks (NDRTs). By applying this model, the critical issues in the HMI design can be clarified in a short time, and the user's habits developed in the previous level of automation can be considered in the new user studies intuitively.



**Figure 2:** Model of user studies in different automation levels.

For the user in Low automation, his attention allocates completely in the circle of Control of vehicle, so the user studies should be focused on helping to maintain the driver's attention on the operational level, for instance alerting the drowsiness [44], monitoring the fatigue [30] and stress [33]. The other more advanced solutions are using technologies to assist the driver minimizing their possible errors and enhance their driving safety, such as a series of user studies related to ADAS [3, 43, 48].

Semi automation is more sophisticated in user studies. As shown in Figure 2, the user's icon is an oval that connects Control of vehicle, Navigation, Circumstances, and also the NDRTs, which means that even though the automation level is increased, but the user's attention resources are diffused in diverse function levels, and the user should also be at the disposal of DDT fall back at any time. The process of the user to take back control from the AVs system is called Take-over, and the time needed to complete this process is Take-over time. Various user studies have been carried out to test the Take-over time [22, 37, 56, 58] and explore the optimal modality to communicate the Take-over requests [4, 5, 36, 38]. On the other end of the oval, the user's attention is allocated in NDRTs, where numerous of user studies have been done in order to understand the impact of NDRTs on driver's performance since in the conditional autonomous driving, human drivers should still be available as the backup [9, 23, 31, 35, 58].

In the case of Full automation, the user's attention is outside the two function levels related to the vehicle itself but occupied by the Circumstances and NDRTs. At this phase, the challenge of user studies has changed from focusing on how to guarantee the driving control, to focus on how to guarantee a better user experience beyond the driving tasks. Firstly, at the early stage of full AVs application in public, the users have not used to the absence of control, and it is natural that they will seek the evidence to trust the AVs. As shown in Figure 2, the blue lines with arrows represent the Human-machine interaction (HMI) between the user and the operational and strategic levels of the driving task which is conducted by the AVs in this case. User studies have shown that keeping the transparency of the decisions and behaviors of the AVs will be helpful to increase the user's trust and confidence towards the AVs [12, 14, 28, 32, 55]. However, the other layer of the impact of the AVs system on the user is seldomly mentioned in the previous researches: the cognitive and emotional effects of AVs behavior and driving styles on users, which should be also addressed because it will affect the comfort and user experience. Then, according to this model, in the near future, the relationship between the NDRTs and users will be the next focus when the trust issue be solved appropriately. Actually, there are already attempts of concept design focusing on this point [31][39], just the user studies are still absent. Finally, the user studies will move to the interactions between different users, between the user and other AVs.

In the previous studies, there was neither user study method considered systematically in different levels of automation, nor a driving simulator developed facing user studies in a wide range of vehicle automation.

### 3 DRIVING SIMULATOR

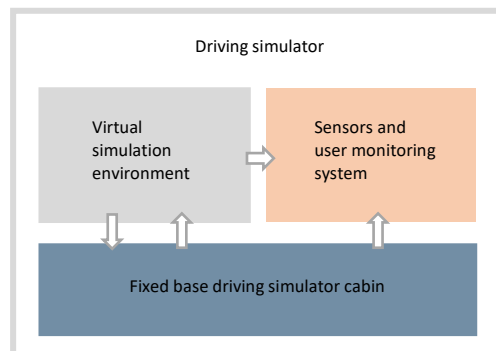
Conducting user studies in driving simulators is the most balanced method and possessing the most varieties of simulating scenarios. In general, there are three types of driving simulators[24][46]:

- Low-level driving simulator: fixed base (FB) simulator with user screens fixed too, see Figure 3(a);
- Mid-level driving simulator: the simulator consists of advanced imaging techniques, a large projection screen, a realistic cab, and possibly a simple motion base, see Figure 3(b);
- High-level driving simulator: the simulator can be accelerated in at least 6 DOFs through a motion platform, see Figure 3(c).



**Figure 3:** The driving simulators. (a)The fixed-base driving simulator of the Delft University of Technology[18];(b) The Toyota driving simulator[13]; (c) The National Advanced Driving Simulator (NADS) in University of Iowa[13].

The driving simulator used in the current study is set up based on the model in Figure 4. It consists of a fixed base physical structure including a set of commercial vehicle controls such as the steering wheel with force feedback, the gear shift lever with automatic transmission, and the brake and accelerator pedals (Logitech G920, [29]). Three 32-inch screens providing 175 degrees field of view show the virtual driving scenario, as shown in Figure 5.



**Figure 4:** Architecture of the current driving simulator and the data flows.

In the driving simulator, the virtual simulation environment is crucial for the quality and fidelity of the images and also the degree of immersion. It is usually generated by simulation software, for example, Unity 3D [51] and IPG CarMaker [21]. Unity 3D is a game engine that allows high flexibility in the car interior design and event scheming, but with limited capacities of vehicle dynamic features simulation. IPG CarMaker enables high fidelity in vehicle dynamic features simulation and the possibility of introducing kinetic models into the virtual simulation environment, but it is limited in the flexibility of HMI design.



**Figure 5:** Set-up of the fixed-base driving simulator.

In this study, both of them are introduced into the case studies, and the choice of which to use is based on a comprehensive consideration of the pros and cons. The data types that can be extracted from the two software are listed in Table 1.

<i>Data type</i>	<i>Unity 3D</i>	<i>IPG CarMaker</i>
Lane position of the vehicle	✓	✓
Steering wheel turning angle(relative)	✓	✓
Routine map	✓	
Vehicle coordinate		✓
Speed variety	✓	✓
Throttle variety	✓	✓
Fuel consumption		✓
Reaction time	✓	

**Table 1:** Checklist of the extracted data types in Unity 3D and IPG CarMaker.

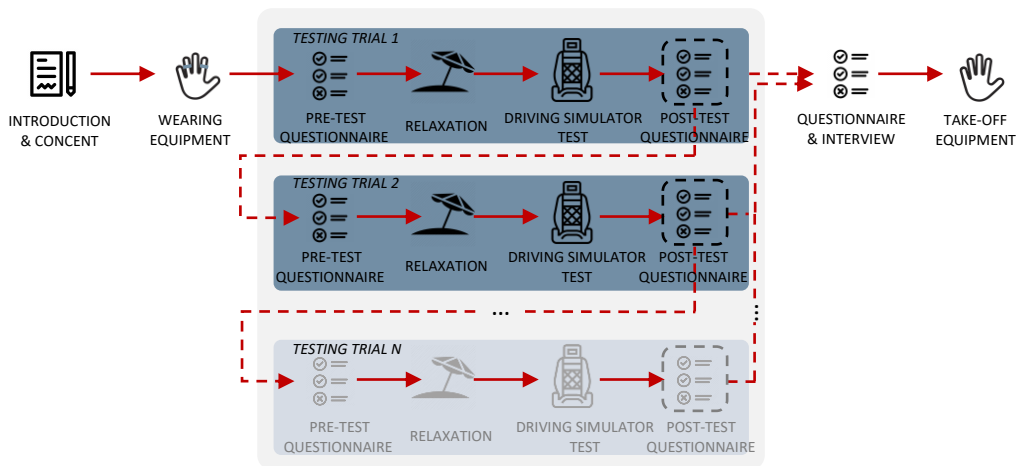
In the sensors and user monitoring system, ProComp Infinity physiological sensors (Figure 5) are for collecting the bio-signal data of the user, Pupil Labs eye-tracking glasses for recording users' eye movements and pupillometry information (Figure 5, [26]), and cameras for recording the users' movements. Physiological signals, such as Electrodermal Activity (EDA) and Electrocardiogram (ECG), and eye-tracking data are used to distinguish the emotional and cognitive states of the users [6, 11, 25, 50]. Each signal should be correlated with a specific psychological parameter which then has been interpreted in an emotional or cognitive state. For example, by measuring the EDA, the stimulus on an emotional level related to a specific event during the experiment can be captured numerically. Hence, a high variation of EDA reflects a strong impact on the parasympathetic system. In other words, if the situation implies that the user is stressed, the increase of EDA indicates the related event enhanced the stress level. Through the analysis of the data of these sensors, the emotional state of the user can be derived with statistical accuracy.

#### 4 CASE STUDIES

In this section, three case studies will be discussed, each of them is deals with a research question in low automation scenario, semi-automation scenario, or full automation scenario, following the



method being introduced in the previous sections. All of the three user studies are carried out with the driving simulator mentioned in section 3. The common workflow for conducting the experiments is shown in Figure 6. Due to the huge individual difference in the physiological aspects in user studies, the experiments are usually organized within-subjects, so that one subject need to experience all the conditions, shown as Testing trials 1 to N. The experimental procedure starts with the introduction of the research, signing the consents, and collecting the basic information of the participants. Then according to the research purpose, the participants need to wear on the different equipment, for instance, the olfactory display in the first case study, and the physiological sensors in all the three cases. After which is the body part of the procedure. Each experimental condition contains four steps: pretest questionnaire, usually is used to acquire the current emotional/cognitive state, a short relax time to calm down, then the driving simulator test, and finally the post-test questionnaire to get the same scales as pretest questionnaire remeasured. The post-test questionnaires sometimes are merged with the pre-test questionnaires in the next trial, in order to simplify the procedure. When all the conditions are conducted, there is a general questionnaire related to the whole experiment and reflecting the entire research purpose proposed to the participant, and in some cases also with interviews involved. Finally, the whole procedure closes with the equipment taken-off from the participant.



**Figure 6:** Workflow of the proposed method to conduct the user study experiment.

#### 4.1 Case study in Low Automation Scenario

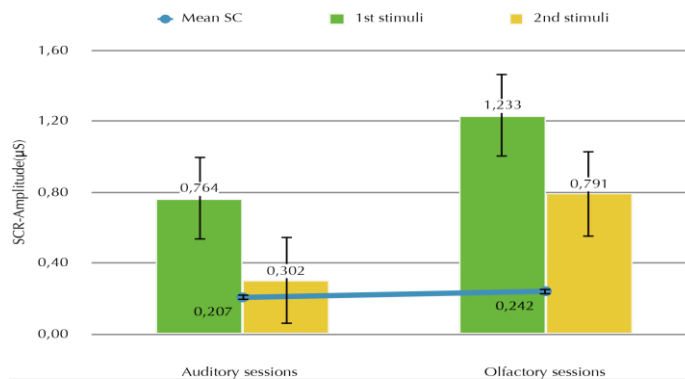
The management of attention (including distraction and inattention) is one of the contributing factors to the major cause of human errors in 80% of the crash events [27]. As mentioned in section 2, to maintain the attention level of users in the control of the vehicle is an essential task in Low automation scenario. Multi-modality interactions have been introduced into the design of HMI in AVs[15]. Olfactory signals have shown the potential in increasing the attention of the user[8], and they are like auditory signals, non-invasive and do not occupy visual modality which should be devoted to the driving task. The olfactory signals are very promising to enable a novel multi-modality interaction in low automation vehicle HMI. Therefore, in this case study the research question is to explore the user behaviors in using the olfactory display in the driving context.

Two experimental tracks were developed: one was a journey with twice olfactory signals as the system alert, and the other one was the same journey with twice auditory signals as the system alert. The twice of alerts of each track was at the same position during the journey. The auditory signals were released by the sound system of the driving simulator, while the olfactory signals were produced through a wearable olfactory display. 15 subjects (average age 30, 6 female) have

participated in the within-subject experiment, in a randomized sequence to conducting the two tracks. Their physiological data were recorded along with the tests.

Figure 7 shows the users' reactions to the two types of signals. The physiological parameter here is the SCR-Amplitude, which is sensitive to the stress, the emotional arousal and the cognitive arousal[59]. The Mean SC value is the overall Skin Conductance value of the whole track. Taking it as a reference, the first, the second olfactory stimulus and their combination created a huge change in the user's emotional and cognitive states, but the olfactory stimuli were more powerful than the auditory stimuli. Need to be noticed that although in both types of stimuli, the second one created less impact to users, but the decline in the olfactory stimuli was less than the auditory stimuli, which implies that olfactory signals lead to less user fatigue effects.

The results suggested that comparing the conventional auditory signals, the olfactory signals have stronger impacts on the user, are potentially become the new elements of the HMI in vehicles.



**Figure 7:** SCR-Amplitude values of users at the sample windows of auditory signals and olfactory signals.

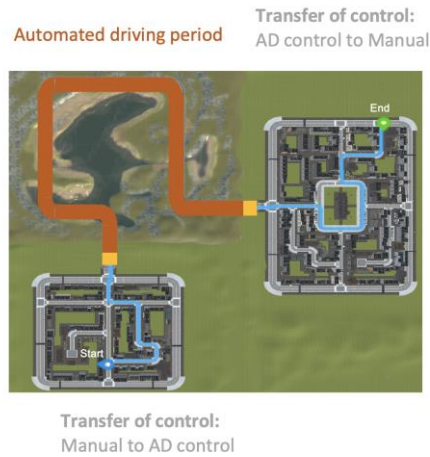
#### 4.2 Case Study in Semi-automation Scenario

As discussed, the critical point in the semi-autonomous scenario for user studies is the transition process of the control. Building a virtual scenario of this process to investigate the users' behavior in the driving simulator is practical. In this case study, the aim is to build up a methodology to study driver's behavior in semi-autonomous driving with physiological-sensors-integrated driving simulators. The research question is to verify that if the user's reaction time can be predicted by his driving performance. A virtual scenario simulating take-over tasks has been implemented by using Unity 3D. In the scenario, two cities connected by a highway is the virtual environment. The task is driving manually from City A to City B (Figure 8), but users need to engage the AI agent to enter the self-driving mode when they enter the highway, and relief the self-driving mode before the exit of the highway, as driving a conditional automated vehicle according to the SAE taxonomies.

As a preliminary study, three healthy participants (Average age 27, Standard Deviation (SD)=1) volunteered for the experiment with more than three years of driving experience. The user's driving performance has been evaluated from a matrix of behavioral indexes (Table 2).

All the data collected and elaborated, have been transformed into a ranking list, making it possible to calculate the overall scores on each one's performance. Finally, all the data have been categorized into three judge indicators, evaluating the driver's performance from three aspects: the speed control, the lane-position control, and the steering wheel control. The third user got highest scores in the driving performance evaluation but was not the one took shortest reaction time. To check the correlation of these three indexes and the reaction time, Kendall's coefficient of concordance was introduced, and the result ( $W = 0.188 < 0.3$ ) showed that these indexes had very low consistency in evaluating the drivers' performance.





**Figure 8:** Driving task routine in the driving simulator.

<i>Behavioral index</i>	<i>Unit</i>	<i>Description</i>	<i>Sampling rate</i>
<i>World position (X, Y, Z)</i>	m	Position of the car in the virtual driving scenario	10 Hz
<i>Speed</i>	Km/h	Speed of the car	
<i>Throttle</i>	[0,1]	Axis of the Throttle pedal	
<i>Brake</i>	[0,1]	Axis of the brake pedal	
<i>Self-driving mode</i>	Boolean	Automated driving system active	
<i>Take-over request</i>	Boolean	AVs initiates a transfer of control	
<i>Heart rate variability</i>	ms	Variation in heartbeats within a specific timeframe	8 Hz
<i>Skin conductance</i>	μS	Electrodermal response of user	

**Table 2:** Behavioral indexes used to evaluate the user’s performance.

It implied that there did not exist a high correlation between the take-over response time and the user performance, which means that we cannot anticipate a driver's reaction time to the take-over request by analyzing his past driving performance.

<i>Judge indicator</i>	<i>Driver 1</i>	<i>Driver 2</i>	<i>Driver 3</i>
<i>Speed control</i>	2	1	3
<i>Lane-position control</i>	1	2	3
<i>Steering wheel control</i>	3	1	2
<i>Reaction time</i>	1	3	2
<i>Scores</i>	7	7	10

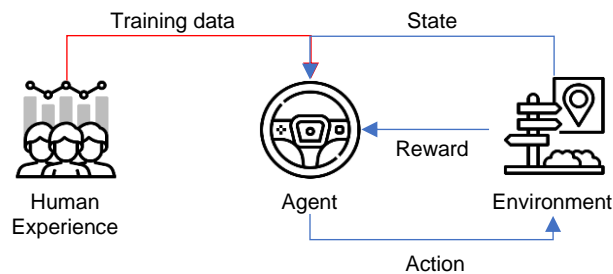
**Table 3:** Result matrix for the driving performance evaluation and reaction times.

### 4.3 Case Study in High Automation Scenario

The driving styles of AVs in high automation level have a strong reliance on their artificial agents. In this case study, two AVs systems with different algorithms behind them are utilized to generate the two driving styles, which are implemented into a driving simulator in order to create the autonomous driving experience. The research aims at exploring the impacts of AVs driving styles on users.

The two AVs systems were based on the Neural Networks (NNs), with the motion behavior layer developed in two methods of Reinforcement Learning (RL) respectively. Figure 9 shows the framework of RL procedure in AVs. NNs were utilized to recognize or classify the driving circumstances. The RL systems determined how the AVs ought to behave as similar as possible to an optimal state. The two systems are:

- Monte-Carlo Policy Gradient (REINFORCE) [54]
- Deep Deterministic Policy Gradient (DDPG) [17]

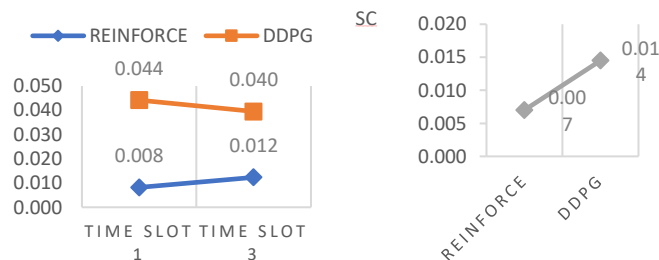


**Figure 9:** Framework of Reinforcement Learning in autonomous driving (adapt from [60]).

Eight students have participated in this experiment, with the mean age of 23.3 (SD=2.1, two females). As for the experimental condition is under full-automation level, no driving experience were required in the participant recruitment. During the test, no NDRTs was involved. Each participant was exposed to both of the two groups (REINFORCE and DDPG), in a random sequence to minimize the potential impact led by the testing order. The users' skin conductance (SC) signal was recorded, and a standard fatigue questionnaire Swedish occupational fatigue inventory (SOFI-20) [1] were requested to be filled just before and immediately after each testing session.

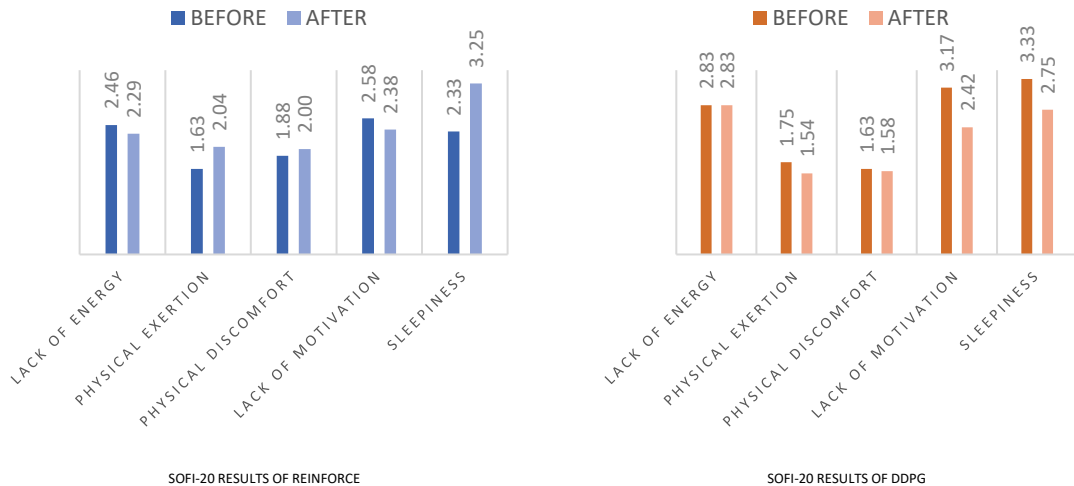
In the data analysis, each test session has been cut into three timeslots for the analysis of physiological data:

- Timeslot 1: acceleration segment;
- Timeslot 2: velocity maintain segment;
- Timeslot 3: deceleration segment.



**Figure 10:** SC data of users. (a) in velocity variation segments; (b) in velocity maintain segments.

SC reflects the changes in the sympathetic nervous system that relates to cognitive arousal, which is a strong predictor of attention and mental workload which may be utilized to detect the driver's awareness from the event and stimuli in the driving situation. From the above diagrams, it can be observed that REINFORCE provided the users with a lower mental workload than DDPG measured in SC, in both the acceleration movement and deceleration movement. A slightly increasing in the mental workload of users was observed between two timeslots of REINFORCE. A decrease in user mental workload occurred with the DDPG system comparing the acceleration phase and the deceleration phase.



**Figure 11:** SOFI-20 results.

Figure 11 shows the results of SOFI-20. It shows that the "Sleepiness" increased across all the participants after a REINFORCE testing session and decreased after a DDPG testing session. A reasonable interpretation could be that according to the users' subjective assessment, they experienced REINFORCE session as a lower mental workload task while getting higher mental workload in the DDPG session to become cognitively aroused.

## 5 CONCLUSION

The present study proposed a systematical method of conducting user studies in various vehicle automation levels through driving simulators and a novel model of user-vehicle interaction in different automation levels. In order to meet the requirements of user studies, the taxonomies of automation levels in AVs have been rearranged into three levels: Low automation, Semi automation, and Full automation. A typical fixed-base driving simulator has been set-up, with the physiological sensors and other measurement tools equipped which enables the experiments to be done following the proposed method.

Three case studies conducted in this driving simulator, have been presented. Each case study emphasized a critical issue in the corresponding automation level. In the Low automation level, drivers' awareness of the circumstances is crucial for on-road safety. Thus, at this level, the user studies are usually focused on maintaining the users' attention level by using multiple stimuli. Olfactory signals have been proven to be effective in generating active cognitive responses in previous studies. The result in this case study demonstrated that the olfactory signals are promising to enable a multi-modality HMI as an improvement of the conventional vision-based HMI. The main

focus from the user study perspective of the Semi-automation level is related to the Take-over scenario, in which the reaction time towards the Take-over Request (TOR) of the user is crucial to maintain coherence and safe drive. In the case study of this level, an insight into the relationship between drivers' performance and their reaction time has been given. The results showed that holding the drivers' driving performance data, the users' reaction time to the TOR is still unpredictable, which suggests the developers not to estimate the reaction time by judging the user's past performance. User's comfort and the possibility of NDRTs are the main concerns in the Full automation level. In the case study of this level, the impact of AVs' driving style onto the users' cognitive workload is investigated. The results imply that the users' cognitive workload can be impacted by the driving style, and specifically, aggressive driving styles are more likely to influence the driver.

The results suggested that the model is applicable and has the potential to give indications for future researches in the field. However, more works need to be completed in the future. To date, the user studies in the driving simulator have always been focused on the single-user modality. However, in the reality and the potential future scenarios, there are more users in one vehicle at the same, for instance, self-driving taxi and autonomous car sharing. In further studies, the interaction should not be limited to the HMI but also involve user-to-user and user-to-other vehicles. Considering this, driving simulators should integrate immersive visualization technologies. For example, combining the motion platform and the physical driver seat together with a head-mounted display, to give the simulator more freedom of creating the scenario, and increase the immersion. Also, new models for the user studies in fully automated vehicles will be established, entailing the new elements in future scenarios.

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