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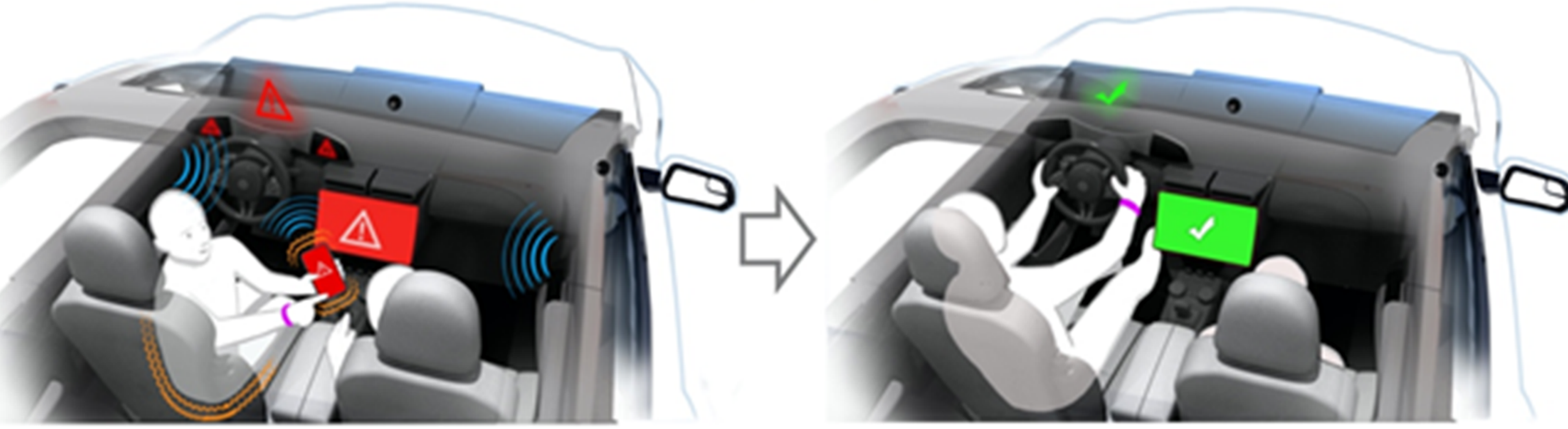

Driver is alerted based on the TOP when a takeover is needed

Driver promptly and safely takes over the vehicle

# Predicting Driver Takeover Performance in Conditional Automation (Level 3) through Physiological Sensing

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CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

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# Predicting Driver Takeover Performance in Conditional Automation (Level 3) through Physiological Sensing

by
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DISCLAIMER

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| **16. Abstract** | | | |
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| The National Highway Traffic Safety Administration (NHTSA) calls for fundamental research on “the driver performance profile over time in sustained and short-cycle automation … and driver-vehicle interface to allow safe operation and transition between automated and nonautomated vehicle operation.” The emerging level 3 autonomous vehicle (AV) has the potential to transform driving because it can perform all aspects of the driving task and allow for complete disengagement of drivers (e.g., sit back and relax) under certain driving scenarios. The vehicle can handle situations that require an immediate response, such as emergency braking. However, this is not fully autonomous, and still requires the driver to be prepared for takeover at all times with a few seconds of warning. Being able to measure and predict the takeover performance (TOP) ahead of time and issue adequate warnings is thus critical to ensure driver comfort, trust, and safety in the system and ultimately acceptance of the technology by different stakeholders. This has not been explored to the extent of establishing complete and irrefutable trust in the autonomous vehicle system and its ability to engage the driver in safe and effective takeover under certain driving scenarios. Therefore, the objective of this project is to perform fundamental research to understand drivers’ capabilities of taking over the vehicle safely and promptly at any time in level 3 automation. This project advances fundamental research in human factors in level 3 AVs. This is achieved through an integrated treatment of the drivers’ TOP measured and predicted through physiological features and driving environment data in level 3 AVs. Thus, the main objective of this research will be to investigate the feasibility of using multimodal physiological features collected from drivers in level 3 AVs under different driving and disengagement scenarios (secondary tasks) to develop a personalized and real-time prediction of TOP. The project will engage a diverse group of students and faculty and develop a research program in an unexplored area of level 3 AVs, leading to substantial advances in how human physiological sensing can be used to understand the driver’s TOP, especially in a personalized manner. Such an understanding can eventually lead to the design of adaptive and personalized alerts that can be integrated in level 3 AVs. | | | |
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**Introduction**

The adoption of Autonomous Vehicles (AVs) is expected to curb traffic congestion, reduce the stress and fatigue of drivers, and improve driving safety [1, 2]. Even though the ideal goal of AVs is to achieve full automation, current AV designs require humans to still play an important role in the driving functions. This is mainly because the current or near future AV designs do not have the reliable relevant technologies [3, 4] to make them fully autonomous and allow complete disengagement of the driver (e.g., insufficient accuracies of computer vision systems [5]). As a result, the current automation systems in vehicles are mostly categorized as "Level 2 Partial Automation", which only provides some driving assistance such as lane centering and adaptive cruise control thus the drivers must always stay alert and prepare for resuming full control of the vehicle [6]. Fatal accidents might be caused if the driver fails to take over control in time such as in the Tesla crash that happened in California [7].

The Society of Automotive Engineers (SAE) stipulates that in "Level 3: Conditional Automation", the vehicle systems are supposed to manage all driving functions under certain conditions and the drivers are required to take over the control only if a request or alert is issued by the car. The drivers are given some freedom in performing secondary tasks such as using their cell phones or other devices, watching videos, and reading. Engagement in these activities will thus further complicate the timely takeover of the vehicles and in some cases result in suboptimal takeover quality [8]. The takeover requests will be given based on the situation awareness of the vehicle systems. Situation awareness indicates that AVs are already equipped with adequate sensors that are able to detect road scenarios. For example, when construction zones [9] or unfamiliar situations (e.g., obstacles) in front of the lane [10] by the onboard sensors of the vehicle, the takeover requests will be given to indicate that the autonomous driving systems may not be able to handle the situations. When the takeover is requested, in order to control the vehicle appropriately, the driver needs to stop any secondary tasks and immediately switch to take over the driving controls of the vehicle to avert any potential accidents [11].

This highlights the importance of interactions between the driver and the vehicle aiming at understanding whether the driver is ready to take over the control of the vehicle (driver's readiness). A key step to achieving this end is to build a system that continuously measures the driver's state, defined as the current cognitive and physical condition of the driver [12]. For example, when the driver is too engaged in the secondary task, it could be reflected in the higher intensity of his/her emotional states (e.g., higher mental workload), thereby leading to poor takeover performance [13]. Therefore, the driver's state can affect the driver's capacity to operate a vehicle safely and react to shifting traffic circumstances thus it can subsequently be used to estimate drivers' takeover readiness and their expected performance [14, 15].

A comprehensive understanding of the driver's state, while they are driving or waiting for the takeover, is thus the key [16-18] to provide important information regarding what are good input features for estimating the takeover readiness and how they should be used. One way to understand in real-time the driver's state is to monitor their physiological responses [19]. Some research has tried to adopt physiological sensors to monitor drivers' Galvanic Skin Response (GSR) [20] and Heart Rate (HR) [21] while they are performing driving tasks. Existing studies revealed that these types of physiological data had the potential to be adopted to bridge the interaction between the driver and the vehicle. The changes in the GSR signal could reflect the changes in sweat gland activity that was reflective of the intensity of the human emotional states [22]. The GSR signal could be further divided into tonic and phasic components. The tonic component was also called the skin conductance level (SCL) and an increase in the SCL could represent the higher intensity of an emotion such as happiness or anxiety. Similarly, HR could be used to provide information on the human autonomic nervous systems [23], for example, a higher HR could also be caused by a stress response [24]. Therefore, it is a good indicator to represent the drivers' emotional changes while they are driving.

Mental states such as work engagement and mental workload are also important indicators of drivers' states. Work engagement is defined as "a positive, fulfilling, work-related state characterized by vigor, dedication, and absorption [25]", and the mental workload is defined as "the 'costs' a human operator incurs as tasks are performed [26]". They are two key mental states to understand the mental fatigue [27] and sense of task involvement [28] of the drivers thereby affect their takeover readiness [29, 30]. For example, a study conducted by Klauer et al. [31] suggested that high engagement in secondary tasks could degrade driving performance. An experiment carried out by Brookhuis and Waard [32] revealed that an optimal mental workload should be maintained to ensure adequate driving performance. However, a review of existing literature revealed that they were not well explored in driving situations. Moreover, the existing studies mainly focused on the effects of alert design on specific physiological responses, while a comprehensive analysis of changes in different physiological responses before and during takeover periods under different takeover scenarios was not investigated. This type of analysis could provide valuable references for the selection of the input features for estimating the drivers' takeover readiness. These raise two important research questions: whether changes in physiological responses prior to and during the takeover periods exhibit a specific pattern? and which types of commonly used physiological data are correlated with different vehicle data that define takeover readiness?

To address the research gaps and incorporate a reliable human-vehicle interaction system in conditional automation, two steps of research are needed: (1) understand the correlation between the drivers' physiological data and takeover activities, and (2) build reliable prediction models for takeover readiness. The scope of this study is to systematically investigate the physiological responses of the drivers under conditional automation.

To achieve the objectives of this project, an experiment was designed using a driving simulator. Different takeover scenarios (i.e., two traffic densities and three takeover events) were incorporated to diversify the driving simulation. The vehicle data and the physiological responses of the participants were collected while they were performing the driving simulation (both before and during a takeover event). The experiment incorporated three types of secondary tasks (observing, 1-back task, and 2-back), three takeover events, and two traffic densities. A low traffic density scenario contains 40 vehicles per mile while a high traffic density scenario has 80 vehicles per mile. The three takeover events are shown in Figure 1 and include: (1) an obstacle in front of the lane, (2) a police car on the right side, and (3) a fake alert. Brain signals, Skin Conductance Level (SCL), and Heart Rate (HR) of the participants were collected while they were performing the driving simulations.

The simulation of the conditional automation was developed using the Unity game engine, and the driving simulator ProSimu T5 Pro was used to incorporate the program. The simulator was equipped with three Samsung 55'' 4K QLED HDR Monitors to display the driving scenarios. Gas and brake pedals were provided to simulate the real driving experience. The participants were allowed to adjust the seat, steering wheel, and pedals to maintain their own preferred driving postures. In addition, the participants were asked to perform secondary tasks while they were waiting for the takeover scenarios. Besides the SCL and HR, brain signals were incorporated in this study to calculate the Frontal Asymmetry Index (FAI) (as an indicator of engagement) and Mental Workload (MWL) of the participants. Fig. 2 shows the positions of the physiological sensors and how the participants performed the secondary tasks. The collected physiological data was then analyzed and compared with respect to different takeover scenarios, takeover readiness, and individuals.

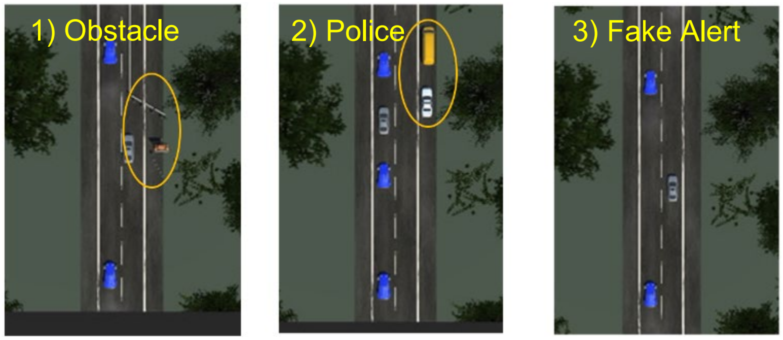


**Fig. 1. Three designed takeover events (from the top view)**

The participants were asked to use a Microsoft Surface to perform the online 1-back or 2-back tasks. The raw data of GSR and HR collected from the sensors could be directly used in the result analysis after straightforward pre-processes such as separating the components (e.g., tonic and phasic components in GSR) and cleaning (e.g., removing the outliers). However, sophisticated analyses were required to obtain the mental workload (MWL) and frontal asymmetry index (FAI) from the raw brain signals collected by the EEG headset. Details regarding the methods used to analyze the collected physiological data are described in the following sections.


**Fig. 2. Physiological sensors during the experiment**

**Findings**

The findings of this study as described below are based on data collected from 20 subjects.

**1. Changes in the physiological responses during the takeover periods**

As shown in Fig. 3, except for the FAI, the values of all types of physiological data, in general, increased during the takeover period (time greater than or equal to zero). The increase in SCL which was a result of sweat gland activity indicated that the sympathetic branch of the autonomic nervous system was highly aroused [33, 34, 35]. In general, the MWL of the participant increased after the alerts and gradually dropped back, while there were no obvious differences between the tendencies with respect to different secondary tasks. By definition, the increase in mental workload indicated the increased mental cost of performing a task [26]. This can be caused by the driver's engagement in the secondary task but also due to the higher stress of the drivers during the takeover period [36]. Similar to SCL and MWL, the values of HR also rapidly increased after the alerts and peaked for around 6s. However, it quickly dropped back to the values close to the prior takeover periods. The secondary tasks prior to the takeover behaviors did not affect the tendencies of the changes in HR. Different from other physiological data, the FAI of the participants did not increase after the alerts. Instead, for the scenarios when the participants were performing 1-back and 2-back prior to the takeover, the FAI slightly decreased after the takeover alerts, while the FAI for the observing scenario did not change during the takeover period. It revealed that the secondary tasks chosen for this study slightly affected the pattern of changes in FAI during the takeover periods. Since a lower FAI indicated that the drivers were less engaged in the tasks they were performing, the decrease in FAI here indicated that the drivers were distracted from driving by the secondary tasks [37].

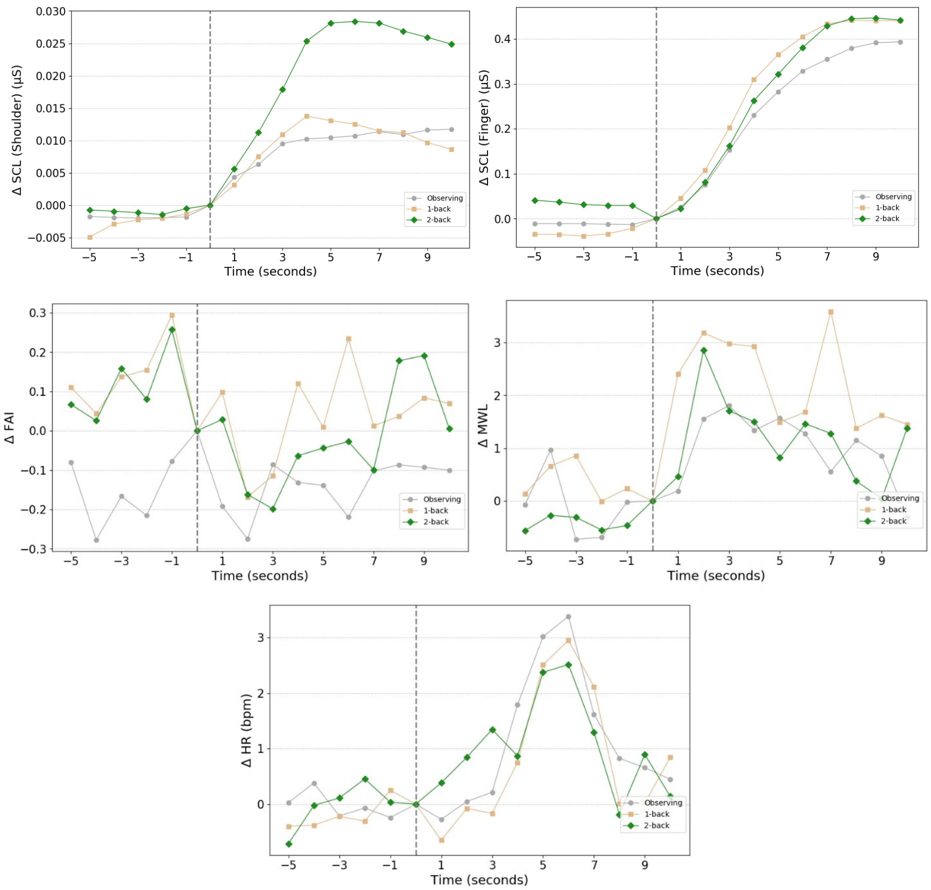


**Fig. 3. Changes in the physiological during takeover behaviors with respect to the secondary tasks**

**2. Effect of a secondary task on average physiological data during the takeover periods**

The mean and standard deviation of the physiological data during the takeover periods are summarized in Table 1. The differences in the specific physiological data concerning the secondary tasks are plotted in Fig. 4. The average FAI of the participants associated with the observing task is higher than the 1-back task (Nemenyi: $p = 0.046$, Cliff's Delta = 0.06) and 2-back task (Nemenyi: $p = 0.002$, Cliff's Delta = 0.08). In contrast, the MWL of the participants associated with 2-back is higher than the observing task (Nemenyi: $p <= 0.033$, Cliff's Delta = 0.04) and 1-back task (Nemenyi: $p = 0.04$, Cliff's Delta = 0.06). In addition, the HR of the participants associated with the observing task is lower than the 1-back task (Nemenyi: $p < 0.001$, Cliff's Delta = −0.156) and 2-back task (Nemenyi: $p < 0.001$, Cliff's Delta = −0.17). As for the SCL collected from the fingers, it indicated that the 1-back task led to a higher average value compared with the observing task (Nemenyi: $p < 0.001$, Cliff's Delta = 0.04) and 2-back task (Nemenyi: $p < 0.001$, Cliff's Delta = 0.05). The statistical analysis showed no differences in the average values of other physiological data concerning the secondary tasks.

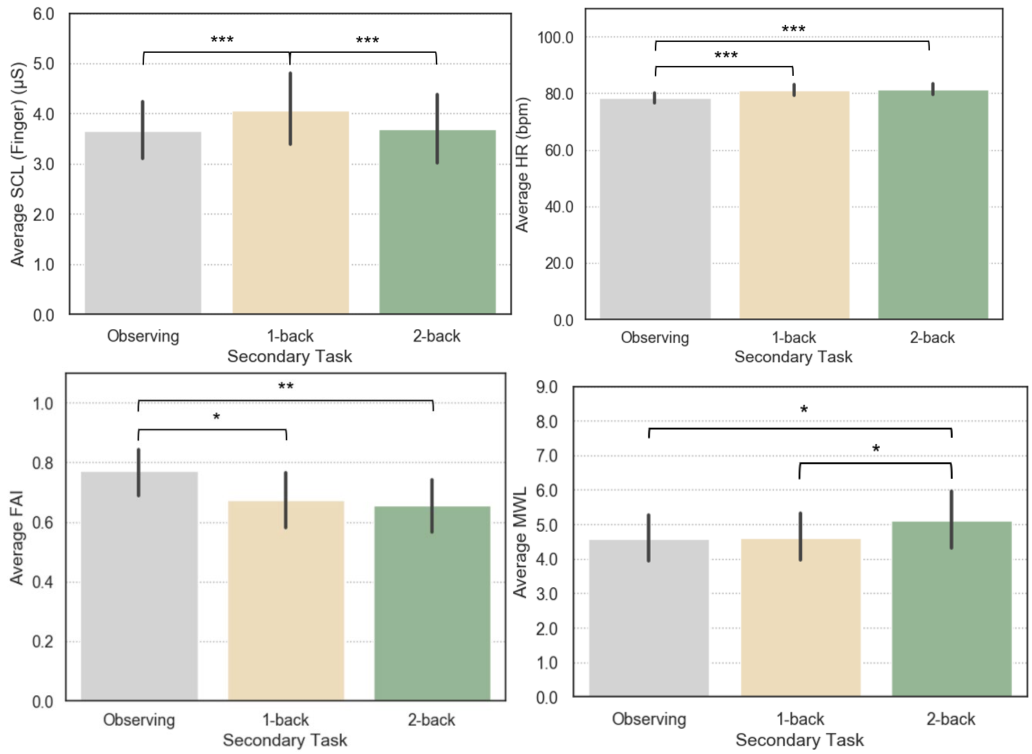


**Fig. 4. Differences in physiological data with respect to the secondary task. The following indication is used for all the figures: *The difference is significant with p-value < 0.05; ** The difference is significant with p-value <0.01; The difference is significant with p-value <0.001.**

**Table 1. Mean and standard deviation of physiological data with respect to different secondary tasks during the takeover period**

| | **Observing** | | **1-back** | | **2-back** | |
|---|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| **SCL (Shoulder) (µS)** | 3.926 | 0.004 | 3.784 | 0.004 | 3.804 | 0.01 |
| **SCL (Finger) (µS)** | 3.661 | 0.144 | 4.07 | 0.163 | 3.688 | 0.169 |
| **FAI** | 0.77 | 0.072 | 0.674 | 0.105 | 0.654 | 0.116 |
| **MWL** | 4.584 | 0.673 | 4.616 | 1.002 | 5.1 | 0.807 |
| **HR (bpm)** | 78.35 | 1.195 | 81.073 | 1.166 | 81.413 | 0.85 |

### 3. Changes in the physiological responses during the takeover periods

As shown in Fig. 5, the differences in the patterns in the changes in the physiological data could be observed in the SCL concerning the takeover events. From the SCL collected from either the shoulders or the fingers of the participants, it could be seen that the peaks and slope of the changes during takeover event 3 (i.e., fake alert) were slower than the other two takeover events. In addition, the FAI slightly decreased after the takeover alerts during all three takeover events. The SCL, MWL, and HR increased with similar patterns regardless of the takeover events, which indicates that the takeover events would not cause obvious effects regarding their changes.

### 4. Effect of takeover events on average physiological responses during the takeover periods

The mean and standard deviation of physiological data concerning different takeover events are summarized in Table 2. Based on the statistical analysis, as shown in Fig. 6, the overall HR of the participants was affected by the takeover events. The average HR of the participants associated with event 1 was higher than event 2 (Nemenyi: $p = 0.02$, Cliff's Delta = 0.03) and event 3 (Nemenyi: $p < 0.001$, Cliff's Delta = 0.08). However, there were no significant differences in the average values of other physiological data concerning the takeover events.

**Table 2. Mean and standard deviation of physiological data with respect to different takeover events**

| | **Event1** | | **Event2** | | **Event3** | |
|---|---|---|---|---|---|---|
| | **Mean** | **S.D.** | **Mean** | **S.D.** | **Mean** | **S.D.** |
| **SCL (Shoulder) (μS)** | 3.79 | 0.006 | 3.823 | 0.007 | 3.907 | 0.004 |
| **SCL (Finger) (μS)** | 3.794 | 0.218 | 3.812 | 0.162 | 3.808 | 0.1 |
| **FAI** | 0.725 | 0.076 | 0.674 | 0.103 | 0.706 | 0.092 |
| **MWL** | 4.782 | 0.804 | 4.8 | 0.771 | 4.699 | 0.879 |
| **HR (bpm)** | 81 | 1.071 | 80.227 | 0.951 | 79.488 | 1.282 |

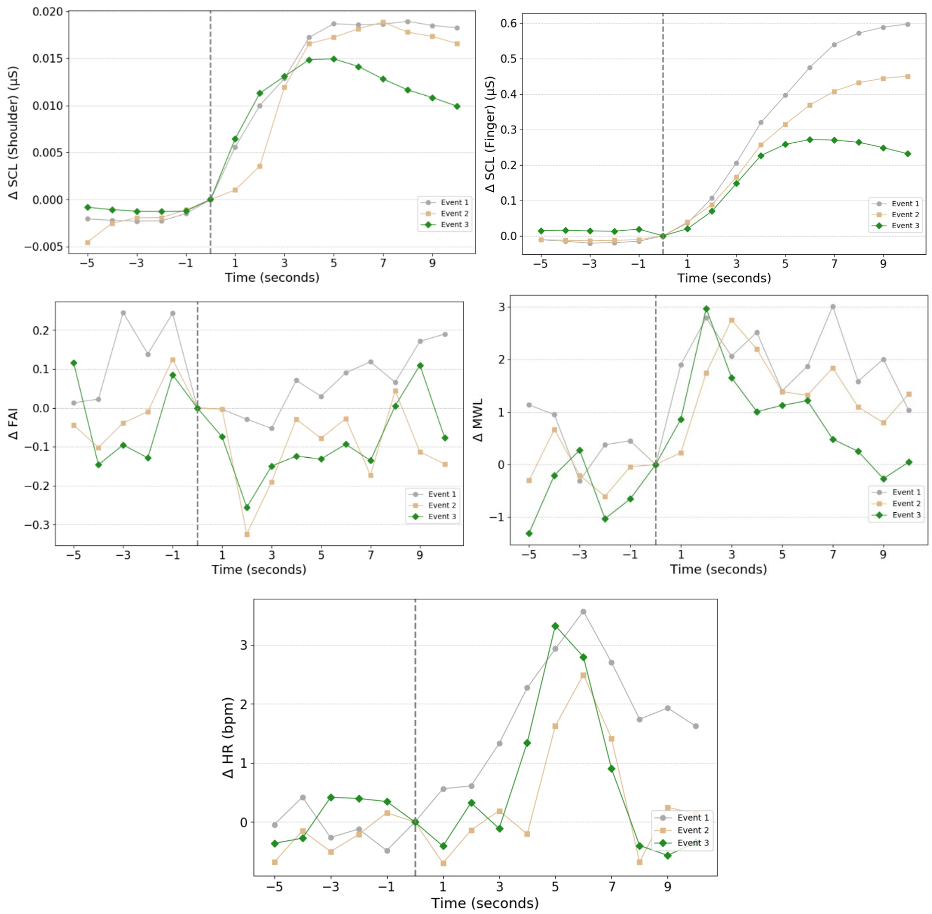


**Fig. 5. Changes in the physiological during takeover behaviors with respect to takeover events**

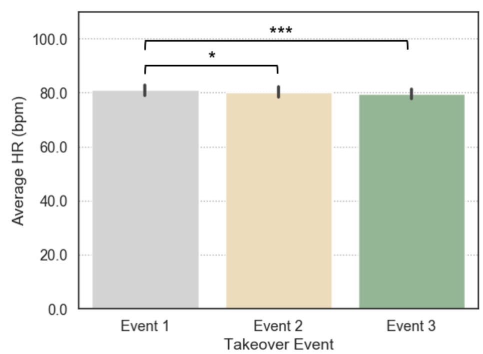


**Fig. 6. Differences in physiological data with respect to takeover events**

## 6. Changes in the physiological responses during the takeover periods

The overall patterns of the physiological responses during the takeover periods remained the same when plotted as per different traffic densities as indicated in Fig. 7. Except FAI, the values of all types of physiological data increased regardless of the traffic densities of the simulation. For example, the peak amplitudes and the slopes of the changes were almost identical in low traffic densities or high traffic densities for most of the physiological data, which indicated that the traffic densities chosen for this study were not a major factor affecting the pattern of these physiological responses of the participants while they were taking over the control of the vehicle. The FAI decreased during the takeover periods in both traffic densities. However, the difference values of the FAI under high traffic density were slightly higher than the low traffic density.

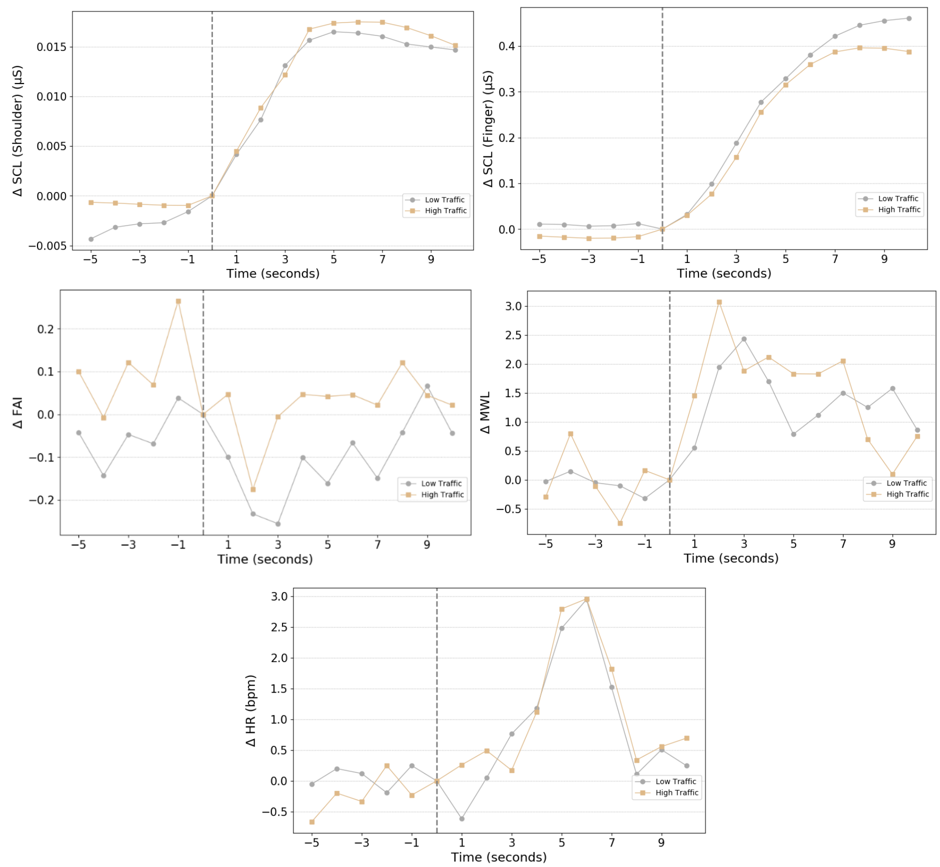


**Fig. 7. Changes in the physiological during takeover behaviors with respect to traffic densities**

**7. Effect of traffic density on average physiological responses during the takeover periods**

The Mean and standard deviation of physiological data concerning different traffic densities are summarized in Table 3. Although the traffic densities did not affect the pattern of the physiological responses during the takeover period, they did affect the average values of specific physiological data such as MWL. As shown in Fig. 8, the average MWL of the participants was higher in high traffic density scenarios than which in low traffic density scenarios (Wilcoxon signed-rank: p = 0.045, Cliff's Delta =

0.03). However, for other physiological responses including FAI, their average values in high traffic density and low traffic density are not significantly different.

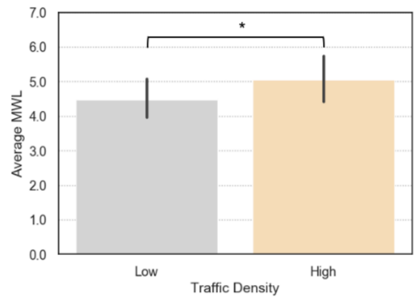


**Fig. 8. Differences in physiological data with respect to traffic densities**

**Table 3. Mean and standard deviation of physiological data with respect to different traffic densities**

| | Low Traffic Density | | High Traffic Density | |
|---|---|---|---|---|
| | **Mean** | **S.D.** | **Mean** | **S.D.** |
| **SCL (Shoulder) (μS)** | 3.806 | 0.005 | 3.874 | 0.006 |
| **SCL (Finger) (μS)** | 3.853 | 0.166 | 3.757 | 0.15 |
| **FAI** | 0.708 | 0.092 | 0.695 | 0.069 |
| **MWL** | 4.478 | 0.652 | 5.046 | 0.899 |
| **HR (bpm)** | 80.143 | 1.069 | 80.332 | 0.992 |

## 8. Correlation between the physiological data, takeover scenario, and vehicle data

In order to have a better understanding of the correlation between physiological data, takeover scenario, and vehicle data and make suggestions for the input features for estimating the takeover readiness, a correlation matrix based on the Pearson correlation was created as shown in Fig. 9. Due to the better heat dissipation and sweat evaporation on fingers compared with the shoulder (covered by clothes), the SCL from fingers was used here. Based on the correlation matrix, both the takeover scenarios and the physiological responses were correlated with the vehicle data that are typically used to determine driving performance. Regarding the takeover scenarios, it can be seen that the takeover event played a more important role in the special vehicle data such as maximum acceleration (i.e., Max Acc) and TTC of the vehicle, while the secondary task and traffic density had less effect on the driving performance. As for the physiological data, the SCL was correlated to the maximum acceleration and the reaction time, while having less correlation to TTC. In addition, the HR is more correlated to the reaction time than the TTC and maximum acceleration. However, there were no specific input features (i.e., physiological data or takeover scenarios) that dominated the correlation to the TOP-related vehicle data (i.e., maximum acceleration, TTC, and reaction time). Moreover, there were no highly correlated input features that needed to be eliminated when being used to make an estimation of the vehicle data. In summary, to make sure a good prediction of takeover readiness, it is suggested that all the features should be incorporated.


**Fig. 9. Correlation matrix between the physiological data, takeover scenario, and vehicle data**

## 9. Role of the individual differences

It can be seen from the previous sections that although there were significant differences in the average values of some types of physiological data based on statistical analysis, the results from Cliff's Delta were overall small. Since Cliff's Delta is fundamentally based on the probability of a value selected from one group that is larger than one selected from another group, personal differences in the physiological data might be the reason for the low values of Cliff's Delta [38]. Therefore, the distribution of the physiological data during the takeover periods with respect to different participants was plotted. As shown in Fig. 10, the ranges of all the physiological data varied a lot across different individuals (with all the Nemenyi p-value $<0.05$), indicating that the specific physiological data of one participant could be much higher or lower than that of another participant. In addition, it is obvious that the physiological responses of some participants were more sensitive than others. For example, the MWL of participants 3, 4, 8, 10, and 19 is more stable than others. It can be seen that the ranges of the SCL collected from the shoulders were very small, which resulted from the less density of sweat glands [39] and smaller oscillation amplitude compared with those from the fingers.

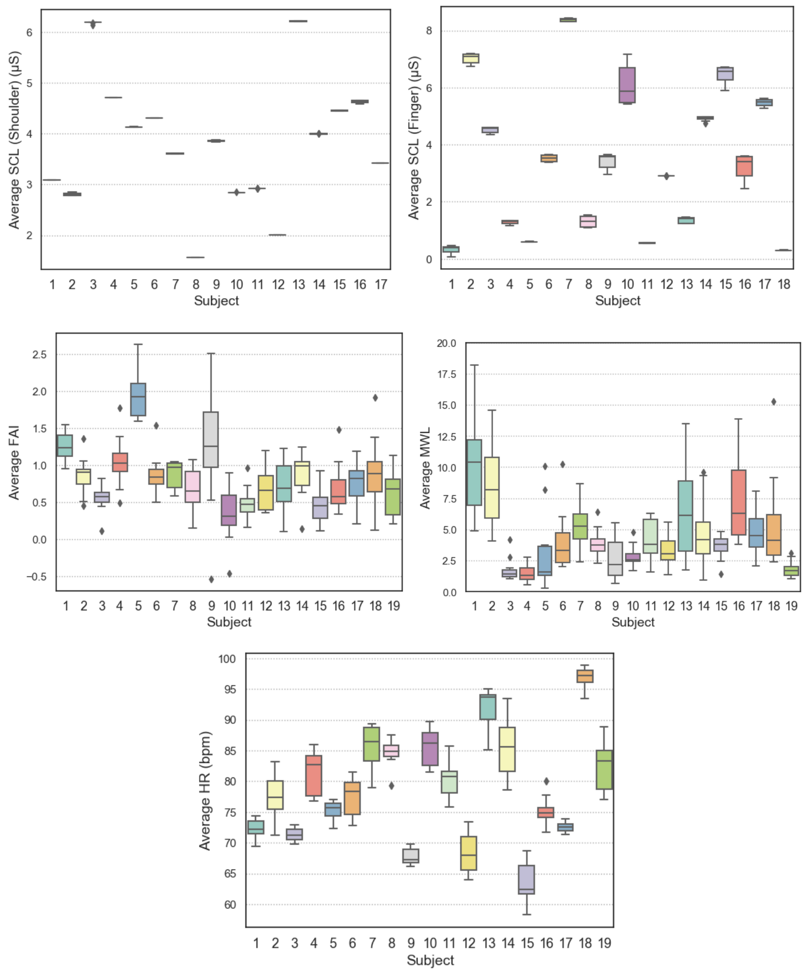


**Fig. 20. Distribution of physiological data as per different participants (the data from specific participants is removed due to data corruption)**

**Recommendations**

This study investigated the effects of takeover activities on the physiological responses of the drivers in conditional automation. To conduct the experiments, a driving simulation program based on Unity and a driving simulator was developed. Different takeover scenarios (e.g., secondary tasks, takeover events, and traffic densities) were incorporated to diversify the experimental design. During the experiments, the typical physiological data (i.e., SCL, MWL, FAI, and HR) was collected from the participants. The tendencies of the changes in different physiological data before and during the takeover periods were plotted and analyzed. The results revealed that the FAI (which represents the engagement of the drivers) slightly decreased during the takeover period when they were shifted from 1-back or 2-back tasks prior to the takeover. In contrast, the MWL, SCL (from shoulder and finger), and HR increased after the alerts of the takeover requests. Compared with SCL and MWL, HR increased rapidly and dropped back fast. A common finding from data collected from the shoulder and finger showed that the SCL increased slower with a lower peak when the takeover alerts were fake. Except for the effect of takeover events on the SCL, the pattern of the changes in physiological data was not affected by the types of takeover events for other physiological responses. However, the analysis of the average values of physiological data during the takeover periods revealed some effects of the takeover events on the drivers. The harder secondary tasks prior to the takeover could lead to lower engagement of the drivers during the takeover periods, indicating that difficult secondary tasks could distract people from preparing for the takeover activities. In contrast, hard secondary tasks prior to the takeover could potentially increase the HR and MWL of the drivers during the takeover periods. In addition, a higher traffic density could increase the MWL of the drivers during the takeover periods. It was also shown that an easier takeover event could result in lower HR for the drivers. Furthermore, the correlation matrix between the physiological data, takeover scenarios, and takeover readiness indicators was discussed. Since personal characteristics might play an important role in the physiological responses, the differences in the physiological data across individuals were analyzed with corresponding suggestions for standardization.

The contributions of this study include: first, an analysis of the potential values of physiological data on conditional automation was conducted, and the results of the changes in physiological responses during takeover periods provided valuable references to support future studies such as selecting the physiological input features to estimate the TOP of the drivers. Second, the effect of takeover scenarios on the overall values of physiological data was analyzed, which could provide additional information regarding the design of the driving simulation in similar studies. Third, the correlation between the physiological data, takeover scenario, and indicators of takeover readiness was analyzed which revealed that although the takeover event, SCL, and HR were slightly more related to maximum acceleration and reaction time, none of the features dominated the takeover readiness. Fourth, the analysis of individual differences emphasized the importance of personal characteristics and the necessity of standardization or normalization when considering using the physiological data from different people for the training of the TOP prediction models.

While the results have provided many insights regarding the potential physiological factors for TOP, there are some limitations in this study. First, although the driving simulator could provide driving experiences that were very close to real driving, it could be new to the participants. Even though the participants were given opportunities to get used to the simulation, the results might still be slightly different from a real driving scenario. However, the design and environment of the simulation were consistent for all participants across all scenarios, the results could still provide valuable references based on the pair-to-pair comparisons. Second, to fairly compare the data collected in different takeover scenarios, the duration and time interval of different takeover scenarios were set to be identical. Nevertheless, the time interval between takeover scenarios and the total driving time in the real world might vary a lot with more randomness. Therefore, the long-term effect of the driving activities on the takeover and physiological responses of the drivers could be investigated in the future. Finally, more diverse groups of participants with distinct driving experiences and age groups would be considered in the future for further understanding of the effect of individual differences. Based on these findings, we aim to explore the feasibility of building TOP prediction models using different learning models in the future. For example, we will explore which types of prediction models would be suitable for a specific set of physiological data and whether time-sequential data could help improve the accuracies.

## Impacts

The emerging level 3 autonomous vehicle (AV) has the potential to transform driving because it can perform all aspects of the driving task and allow for complete disengagement of drivers (e.g., sit back and relax) under certain circumstances. The vehicle can handle situations that require an immediate response, such as emergency braking. However, this is still not fully autonomous and requires the driver to be prepared for takeover at all times with a few seconds of warning. To achieve safe driving behaviors under all conditions (known and unforeseen), humans must trust automated systems to make the right decisions. In return, these systems must decipher a human driver's readiness to intervene, as well as respond to a range of driver skill levels and human engagement during takeover scenarios. This project is investigating how to measure and predict the takeover performance (TOP) ahead of time and issue adequate warnings, which is critical to ensure driver comfort, trust, and safety in the system and ultimately acceptance of the technology by different stakeholders.

The contributions of this study include: first, a systematic analysis of the potential values of physiological data on conditional automation was conducted, and the results of the changes in physiological responses during takeover periods provided valuable references to support future studies such as selecting the physiological input features to estimate the TOP of the drivers. Second, the effect of takeover scenarios on the overall values of physiological data was analyzed, which could provide additional information regarding the design of the driving simulation in similar studies. Third, the analysis of individual differences emphasized the importance of personal characteristics and the necessity of standardization or normalization when considering using the physiological data from different people for the training of the TOP prediction models.

The work on this project has produced the following products:

- Deng, M., Gluck, A., Zhao, Y., Li, D., Menassa, C., Kamat, V. and Brinkley, J. (2023). "A Systematic Analysis of Physiological Responses as Indicators of Driver Takeover Readiness in Conditionally Automated Driving." Accident Analysis and Prevention. Elsevier. In Review.
- Gluck. A., Deng. M., Zhao. Y., Menassa. C., Li. D., Brinkley. J. and Kamat. V. (2022). "Exploring Driver Physiological Response During Level 3 Conditional Driving Automation." In the proceedings of the 2022 International Conference on Human Machine Systems (ICHMS). Orlando, FL. https://ieeexplore.ieee.org/abstract/document/9980597
- Menassa, C., Kamat, V. and Brinkley, J., Deng, M., Gluck, A., Zhao, Y., Li, D., (2022). "Can Physiological Sensing Indicate Driver Takeover Abilities in Conditional Level 3 Automation?" Research Review Presentation. UM Center for Connected and Automated Transportation. March 09, 2022. Copy of presentations can be found here: https://www.dropbox.com/scl/fi/25s41t1yueb190la888ck/2022_03_09-RR-with-Carol-Menassa-and-Vineet-Kamat-Slide-Deck.pdf?rlkey=biq6zayemz0t7vyyqifq41kyx&dl=0 and video https://ccat.umtri.umich.edu/events/past/research-review-driver-takeover/#youtube
- Deng, M., Gluck, A., Zhao, Y., Menassa, C., Kamat, V., Li, D., Brinkley, J. "*Data for Predicting Driver Takeover Performance in Conditional Automation (Level 3) through Physiological Sensing* [Data set]." University of Michigan - Deep Blue Data. https://doi.org/10.7302/b312-3t56

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