

Evaluating the Impacts of Driver's Pre-warning Cognitive State on Takeover Performance Under Conditional Automation

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Abstract

To design better fallback procedures and enhance road safety for conditionally automated vehicles (SAE Level 3), it is important to understand the factors that affect driver's takeover performance (i.e., driving performance while resuming manual control). This study investigates the impacts of driver's pre-warning cognitive state (i.e., before the issuance of a takeover warning) on takeover performance. Most existing studies assess takeover performance by independently analyzing driving performance indicators (e.g., minimum time-to-collision and maximum deceleration), and thereby ignore their associated interdependencies. This study proposes a novel comprehensive takeover performance metric, Takeover Performance Index (TOPI), that combines multiple driving performance indicators representing three aspects of takeover performance: risk of collision, the intensity of the driver's response, and trajectory quality. Further, the driver's pre-warning cognitive state is estimated by analyzing neurophysiological data (i.e., brain electrical activity) measured using an electroencephalogram (EEG) for 118 participants in driving simulator experiments. Linear mixed models are estimated for takeover performance to analyze its linkages to the driver's pre-warning cognitive state, novelty in takeover experience (i.e., prior experience with a takeover situation), type of takeover warning (i.e., non-mandatory takeover vs. mandatory takeover), age, and driving experience. In this study, most drivers intervened in non-mandatory takeover scenarios and exhibited poor takeover performance. We observed three crashes across 287 runs. The study results show that takeover performance decreases with age but increases with driving experience when the driver is under certain pre-warning cognitive states, including fatigue, drowsiness, passive attention, and low level of alertness. They also illustrate that the novelty in takeover experience and mandatory takeover warning negatively affects takeover performance. The study findings provide insights for developing operator training and licensing strategies, designing regulations for the use of automated vehicles, and factoring driver cognition in designing fallback procedures in automated vehicles.

Keywords: Automated driving, Takeover performance, Driver cognition, Electroencephalography (EEG), Driving simulator

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1. Introduction

Advances in automated vehicle technologies promise faster, more accessible, more convenient, and fuel-efficient mobility (Chao and Kratsios, 2020). But their greatest potential lies in the capability to continuously monitor surroundings and make driving decisions that can significantly enhance road safety by reducing the possibility of human error, which often results from distraction or fatigue (Chao and Kratsios, 2020). SAE Level 2 or partially automated vehicles that assist drivers with lane-keeping and/or adaptive cruise control are already available commercially. However, drivers in these vehicles are expected to remain fully engaged with the driving task and monitor the system and road environment at all times (SAE J3016, 2018). As the technology matures to SAE Level 3 or conditional automation, drivers will assume a more passive role as they can engage in non-driving related tasks (NDRTs) while the vehicle performs most of the dynamic driving tasks (SAE J3016, 2018). However, drivers must promptly be able to resume vehicle control as a fallback option if it issues a takeover warning for venturing out of its operational bounds. Previous studies have shown that the monotonous monitoring of partially automated driving systems often results in passive fatigue, vigilance decrement, and mental underload that can negatively impact the driver’s takeover performance in critical situations (Körber et al., 2015; Young and Stanton, 2002). In addition, concerns regarding increased driver distraction and reduced situational awareness due to engagement in NDRTs emerge in conditionally automated vehicles (de Winter et al., 2014). Hence, it is important to understand the cognitive factors that influence driver’s takeover performance in conditionally automated vehicles and incorporate them in designing fallback procedures.

This study investigates the impacts of driver’s pre-warning cognitive state (i.e., before the issuance of a takeover warning) on takeover performance under conditional automation. Section 1.1 presents a brief literature review related to driver cognition in automated vehicles and discusses the importance of factoring driver’s pre-warning cognitive state in takeover performance. Further, to benchmark the role of driver’s pre-warning cognitive state in takeover performance, a comprehensive metric is required to capture the overall driving performance and road safety during the takeover event. However, most existing studies ignore the interdependencies between the associated driving performance indicators (e.g., minimum time-to-collision and maximum deceleration) by analyzing them independently. Hence, we propose a novel comprehensive takeover performance metric, Takeover Performance Index (TOPI), that combines multiple driving performance indicators representing three aspects of takeover performance: risk of collision, the intensity of the driver’s response, and trajectory quality.

Next, we discuss the literature on driver’s cognitive states and their role in takeover performance. In Section 1.2, we review various indicators used to assess takeover performance, discuss related shortcomings, and distinguish the TOPI metric from the prior efforts to overcome these shortcomings. Then, we summarize the study objectives and contributions in Section 1.3.

1.1. Driver cognition in automated vehicles

In partially automated vehicles, driver cognitive states such as passive fatigue and hypovigilance can lead to slower reactions to takeover warnings and/or unsafe driving maneuvers (Körber et al., 2015). Conditional automation further aggravates these issues by introducing NDRT-induced distraction and resulting decrease in situational awareness (Capalar and Olaverri-Monreal, 2018; Radlmayr et al., 2014). Jarosch et al. (2019) summarized the effects of NDRT on drivers’ motoric, sensory, and cognitive abilities as well as their arousal levels under conditional automation. Previous studies have investigated the changes in driver’s cognitive states during partially and conditionally automated driving using subjective self-reported surveys as well as objective physiological indicators, typically after encountering a takeover event or a similar critical situation (see de Winter et al., 2014 for a review). A few studies have used self-reported

surveys to evaluate different aspects of driver cognition; for example, NASA Task Load Index (NASA-TLX) and Rating Scale Mental Effort (RSME) to assess mental workload (de Winter et al., 2014), Dundee Stress State Questionnaire (DSSQ) to assess task engagement and mind wandering (Heikoo et al., 2018; Körber et al., 2015), Karolinska Sleepiness Scale (KSS) to assess fatigue and drowsiness (Solís-Marcos et al., 2017), and Situation Awareness Rating Technique (SART) to assess situational awareness (Tanshi and Soffker, 2019). However, self-reported surveys are conducted after the takeover event and suffer from several memory biases (e.g., misattribution and transience) (Schacter, 1999), which reduces their ability to accurately estimate the driver's cognitive state before and during the takeover event. Naujoks et al. (2018) partially addressed these issues by using two expert raters to observe recorded experiment videos to subjectively assess driver cognition (i.e., fatigue and workload) and motivation to engage in NDRT during Level 3 automated driving. However, expert rater assessments are prone to several errors that arise from their subjective nature, such as the halo effect (Engelhard Jr, 1994).

To avoid the aforementioned limitations of subjective measures of driver cognition, objective physiological indicators, including eye-related metrics, skin conductance, and heart rate and its variability, have been analyzed to estimate the driver's cognitive state. Studies have shown that increased eye blink rate, increased eye blink duration, and decreased pupil diameter are correlated with vigilance decrement under partial automation (Körber et al., 2015). Drivers also exhibit a lower eye blink rate when facing a critical takeover situation compared to a non-critical situation under partial automation, likely due to a sudden increase in workload (Merat et al., 2012). Similarly, lower heart rate, reduced skin conductance, and increased percentage eye closure (PERCLOS) are associated with reduced driving workload (de Winter et al., 2014). Alrefaie et al. (2019) found that driver's heart rate spikes when they are prompted to take over vehicle control. Some studies have also analyzed brain electrical activity patterns measured using electroencephalogram (EEG) to estimate driver stress, attention, mental demand, and vigilance decrement (Lee and Yang, 2020; Solís-Marcos et al., 2017). Despite evidence of the driver's cognitive state affecting takeover performance, previous studies focus on evaluating the changes in driver's cognitive state during and after a takeover event (de Winter et al., 2014) rather than analyzing the impacts of driver's pre-warning cognitive state on takeover performance. Marberger et al. (2018) proposed a framework to predict driver state (motoric, sensory, and cognitive) before a takeover using the current driver state within a sufficient time budget for the automated vehicle to issue a request to intervene (takeover request). However, they did not provide details about the driver state (including cognitive state) transition process and its impacts on takeover performance. A few studies have manipulated driver's pre-warning cognitive states (e.g., attention, mental workload, and fatigue) in conditionally automated vehicles to investigate their effects on takeover performance by varying experimental driving conditions such as traffic density (Gold et al., 2018) and type of NDRT (Jarosch, 2020; Kim et al., 2018), or by controlling driver's cognitive state through sleep deprivation (Vogelpohl et al., 2019) or intoxication (Wiedemann et al., 2018). But these studies do not analyze the driver's pre-warning cognitive state immediately before a takeover event, which can significantly impact takeover performance. To address this gap, we estimate the driver's pre-warning cognitive state, which is affected by driving-related factors (e.g., maintaining situational awareness during automated driving) and NDRT-related factors (e.g., expending cognitive resources to execute the task), and can impact their takeover performance. We define the pre-warning cognitive state as an aggregate of multiple cognitive constructs related to alertness (i.e., readiness to receive and process information), arousal (i.e., non-specific physiological activation in relation to sleep-wake states, including drowsiness and fatigue), attention (i.e., focused physiological activation towards specific information), and mental workload (i.e., cognitive effort required to perform a task) (Cain, 2004; Lindsley, 1988; Oken et al., 2006). This study estimates the driver's pre-warning cognitive state by analyzing driver's neurophysiological indicators (i.e., brain electrical activity) measured using EEG in driving simulator experiments and explicitly models its impacts on takeover performance in conditionally automated vehicles. Previous studies

1 have estimated latent cognitive state in driving and non-driving contexts using different EEG measures,
2 including coherence (Aftanas and Golocheikine, 2001), event-related potentials (Solís-Marcos et al., 2017),
3 and frequency band powers (Agrawal and Peeta, 2021; Lal et al., 2003). This study analyzes frequency
4 band powers of EEG signals (or “EEG band powers”) to estimate several cognitive constructs in an
5 aggregate sense. We leverage past knowledge to infer different constructs of the cognitive state by analyzing
6 patterns of EEG band powers in different regions of the brain (Agrawal et al., 2020; Agrawal and Peeta,
7 2021). Although gathering EEG data in real-world driving is less practical compared to other physiological
8 data (e.g., eye-tracking and heart rate measures), this study uses EEG data as it can estimate a more detailed
9 profile of driver cognition by analyzing electrical activity patterns in different regions of the brain (Abhang
10 et al., 2016; Agrawal et al., 2020), especially in laboratory settings. Thus, it can provide more
11 comprehensive insights on the underlying factors that affect takeover performance, which may not be
12 possible by using other physiological indicators. Auto manufacturers can use these insights to improve the
13 design of fallback procedures in conditionally automated vehicles. It will also assist policymakers to
14 incorporate drivers’ cognitive aspects in developing policies that regulate the use of these vehicles.

15 Previous studies have shown that several other factors such as type of takeover situation (Radlmayr,
16 2020; Radlmayr et al., 2014), type of takeover warning (Lu et al., 2019), learning effects (Gold et al., 2018),
17 and road and traffic conditions (Gold et al., 2016) affect takeover performance. In this study, we investigate
18 the impacts of some of these factors, including the type of takeover warning and novelty in takeover
19 experience (i.e., learning from driver’s first experience with a takeover situation), on takeover performance.
20 Further, the effects of age on takeover performance remain unclear in the literature, most likely due to the
21 counterbalancing effects of slower processing and more cautious driving style with an increase in age
22 (Zhang et al., 2019). Thus, we also analyze the interaction effects of age and its covariate (i.e., driving
23 experience) with driver’s pre-warning cognitive state to analyze their counterbalancing effects on takeover
24 performance.

25 *1.2. Takeover performance measures*

26 In recent years, several studies have emerged in the context of modeling takeover performance under
27 conditional automation. Typically, these studies model takeover performance using human performance
28 (e.g., reaction time) and driving performance (e.g., minimum time-to-collision) indicators (Dogan et al.,
29 2019; Radlmayr et al., 2014). Among human performance indicators, reaction time is the most commonly
30 used measure to evaluate takeover performance. Several variants of reaction time have been proposed,
31 including takeover time, time-to-eyes-on, and time-to-hands-on, which respectively measure the time
32 elapsed from the issuance of a takeover warning until the driver resumes manual control of the vehicle, the
33 first gaze at the road, and the first touch at the steering wheel (Zeeb et al., 2016). However, faster reaction
34 time does not necessarily entail safe driving maneuvers, especially in time-critical takeover situations (Gold
35 et al., 2013). Other human performance measures such as visual performance (e.g., eye gaze dispersion)
36 (Gold et al., 2016) have also been used to assess takeover performance. However, the aforementioned
37 measures evaluate driver’s readiness rather than the actual driving performance and overall takeover quality
38 (i.e., the quality of driving maneuver during a takeover event), which directly determines road safety.

39 Several studies have evaluated takeover quality to assess takeover performance using three aspects of
40 driving performance: risk of collision, driver’s response, and trajectory quality. First, related to collision
41 risk, crash probability (Gold et al., 2018) and the number of collision occurrences (Olaverri-Monreal et al.,
42 2018) have been used to estimate of risk of collision in takeover situations. Minimum time-to-collision
43 (TTC) is another well-established metric to evaluate the risk of collision (Radlmayr, 2020; Radlmayr et al.,
44 2014), with a lower value of minimum TTC indicating a higher risk of collision. Other studies have used
45 minimum space and time headways to quantify traffic safety during a takeover (Dogan et al., 2019;

Wiedemann et al., 2018). Second, as driver's steering and braking responses have direct impacts on vehicle dynamics, several studies have analyzed driver response to evaluate takeover quality. Steering wheel-related interactions have been studied using frequency analysis, mean percentage change, standard deviation, and maximum value of steering wheel angle (Alrefaie et al., 2019; Dogan et al., 2019; Naujoks et al., 2019; Olaverri-Monreal et al., 2018). Brake pedal-related interactions have been analyzed using brake application probability, frequency of brake application, average longitudinal deceleration rate, and maximum longitudinal deceleration rate (Dogan et al., 2019; Gold et al., 2018; Körber et al., 2016; Olaverri-Monreal et al., 2018; Radlmayr, 2020). Third, some studies have analyzed trajectory quality using the longitudinal and lateral aspects of vehicle trajectory. While longitudinal trajectory mainly informs about the risk of rear-end collisions, lateral trajectory informs about the risk of the vehicle drifting out of the road or collision with other vehicles in the side lanes. Previous studies have evaluated longitudinal trajectory quality using mean percentage change in vehicle speed, average speed, and minimum vehicle speed (Alrefaie et al., 2019; Happee et al., 2017; Naujoks et al., 2019), and lateral trajectory quality using maximum lateral acceleration, deviation of lateral road offset, and lane change time and speed (Dogan et al., 2019; Doubek et al., 2020; Körber et al., 2016; Mok et al., 2015). Happee et al. (2017) used additional measures, including obstacle clearance, roadside clearance, and lateral overshoot (going past the target lateral position), to further evaluate the trajectory quality during a takeover event. Qualitative assessment of vehicle trajectories (e.g., visual inspection of trajectory plots) has also been used in past work (Gold et al., 2013). Doubek et al. (2020) compared vehicle trajectories from driver intervention after a takeover request to the 'optimal' trajectories generated by an algorithmic trajectory planner designed to maximize route progress, safety, and comfort.

In summary, while past studies have assessed takeover performance using multiple indicators, each indicator is often analyzed independently. Thus, they are limited in their ability to provide an overall assessment of takeover performance, especially from the perspective of takeover quality, as they ignore the interactions and interdependencies between these indicators. For example, a higher rate of longitudinal deceleration, which generally represents poor takeover performance, can result in a longer minimum TTC, which generally represents a good takeover performance. Radlmayr et al. (2018) proposed an integrative framework, called the take-over performance score or TOPS, that aggregates different takeover performance measures to three dimensionless parameters representing vehicle guidance (e.g., collision occurrence and minimum TTC), driver's mental processing (e.g., reaction time), and subjective ratings of takeover situation (e.g., perceived criticality and perceived complexity). However, TOPS has certain limitations: (i) as acknowledged by the authors, it represents differences in takeover performances and not necessarily their quality (good or bad), (ii) each parameter is calculated by linearly combining its corresponding indicators without accounting for their nonlinear relationships, and (iii) the vehicle guidance parameter combines generic vehicle dynamics indicators, and thereby, does not consider that different takeover situations entail different safe driving maneuvers. In this context, our study proposes Takeover Performance Index (TOPI), a novel comprehensive takeover performance metric that combines multiple driving performance indicators while partly accounting for their interdependencies. The proposed framework to compute TOPI is flexible and can be adapted to different takeover situations as discussed in Section 3.

1.3. Study objectives and contributions

In summary, this study: (i) designs driving simulator experiments for two types of takeover warnings (i.e., non-mandatory takeover vs. mandatory takeover) in simulated conditionally automated vehicles, (ii) estimates driver's pre-warning cognitive state using objective neurophysiological indicators (i.e., EEG data), (iii) proposes a novel framework to compute a comprehensive takeover performance metric that combines multiple driving performance indicators representing three aspects of takeover performance, and

(iv) analyzes the impacts of driver’s pre-warning cognitive state (e.g., fatigue and attention), age, driving experience, novelty in takeover experience, and type of takeover warning, on takeover performance.

The study contributions are as follows. First, the current literature analyzes several indicators (driving performance and others) to evaluate takeover performance but lacks a single metric that can be used to comprehensively assess takeover performance. We propose a novel framework to compute a comprehensive takeover performance metric to bridge this critical gap by combining multiple driving performance indicators representing different aspects of takeover performance. Further, the proposed framework facilitates the standardization of takeover performance, which will enable researchers, auto manufacturers, and regulatory agencies to assess takeover performance more consistently. Second, to the best of our knowledge, this study is the first effort to directly analyze the impacts of driver’s pre-warning cognitive state on takeover performance. We also analyze the interaction effects of individual characteristics (i.e., age and driving experience) with the driver’s pre-warning cognitive state, which will provide valuable insights to policymakers for developing operator training programs and designing licensing and other regulatory strategies for conditionally automated vehicles. Third, we estimate driver’s pre-warning cognitive state using physiological indicators, which circumvents memory biases associated with subjective self-reported measures, and thereby, provides a more accurate estimate of driver cognition. Further, by using EEG data instead of other physiological indicators, we are able to estimate a more detailed profile of driver cognition.

The remainder of the paper is organized as follows. Section 2 discusses the experimental design and data collection procedures. Section 3 presents the framework for computing a comprehensive takeover performance metric and compares it with an existing integrative takeover performance metric. Section 4 discusses the statistical analysis methods used to evaluate the impacts of driver pre-warning cognitive state and other factors on takeover performance. Section 5 summarizes the analysis results and study findings. Finally, Section 7 concludes this paper by summarizing the study contributions and discussing their potential impacts on academia, industry, and government. We also discuss the limitations of this study and provide some future research directions in the final section.

2. Methodology

2.1. Apparatus

2.1.1. Driving simulator

The study was conducted using a medium-fidelity driving simulator (AVSimulation, 2020) with a full-scale driving cockpit and force feedback on the steering wheel, as shown in Figure 1. The driving environment with 120° field-of-view was projected on three LCD screens. Two side-view and rear-view mirrors are presented on the screens. A four-lane divided highway replicating the road curvatures of sections of the U.S. Interstate 65 (I-65) between West Lafayette, IN and Chicago, IL, was created using SCANeRStudio® 1.7 software. This was done to avoid generating a driving environment with a completely straight road, which may reduce the ecological validity of the study by artificially reducing the cognitive effort required to monitor the driving environment. The speed limit was set to 105 kph (about 65 mph). The driving environment also featured dynamic ambient traffic, which was slowly dissipated before the takeover event (see Section 2.2.1 for details). Driving data was collected at 20 Hz frequency.

2.1.2. Automated driving system

The study used a Level 3 automated driving system (ADS) that could perform both longitudinal and lateral control on the highway. It observed the speed limit and stayed in the right-most lane unless it had to

1 pass slower-moving vehicles in the lane. It also provided two types of takeover warnings, an uncertainty
2 alert and a takeover request (TOR). Note that the term ‘takeover request’ used in this study is synonymous
3 with the term ‘request to intervene’ recommended by SAE J3016 (2018). The warnings were delivered in
4 the auditory format using two multimedia speakers that were positioned on each side of the driving cockpit
5 below the screens. An uncertainty alert (presented as a single auditory chime) denoted that the ADS is
6 unsure if it could navigate the road scene ahead and prompted the driver to redirect their attention on the
7 road without the need for active intervention (non-mandatory takeover). A TOR (presented as three auditory
8 chimes in quick succession) denoted a system failure that required the driver to resume vehicle control as
9 soon as possible (mandatory takeover) to avoid potential road safety hazards. In this study, a TOR was
10 always preceded by an uncertainty alert.



11
12 **Figure 1 Driving simulator and NDRT**

13 *2.1.3. Non-driving related task (NDRT)*

14 To simulate visual and manual distraction for the participants, an NDRT was developed that consists
15 of a number transcription task delivered on a touchscreen tablet. The tablet was supported by a stand that
16 was affixed to the base of the simulator and was positioned near the center console (see Figure 1). The
17 participants completed a single NDRT task by inputting two six-digit numbers with the mathematical
18 operator shown on the left side of the tablet screen into a calculator interface and pressing submit when
19 done. No advanced numeracy skills were needed. Numeric characters were chosen over alphanumeric
20 characters to avoid potential language-specific biases.

21 *2.1.4. Electroencephalogram (EEG)*

22 Participants’ brain electrical activities were recorded during the simulated runs with a sampling rate of
23 256 Hz using the B-Alert X24 electroencephalogram (EEG) (Advanced Brain Monitoring, 2017). Nineteen
24 EEG electrodes (or EEG channels) were placed according to the International 10-20 system (Klem et al.,
25 1999), as shown in Figure 2. An EEG channel’s prefix identifies its corresponding brain regions, that is,
26 prefrontal lobe (Fp), frontal lobe (F), parietal lobe (P), temporal lobe (T), occipital lobe (O), and central
27 sulcus (C). The EEG channel’s suffix identifies its hemisphere, that is, left (1, 3, 5, 7), right (2, 4, 6, 8), and
28 midline (z). A1 and A2 channels represent the mastoids that are used as references for measuring the power
29 of the electrical signal at the EEG channels.

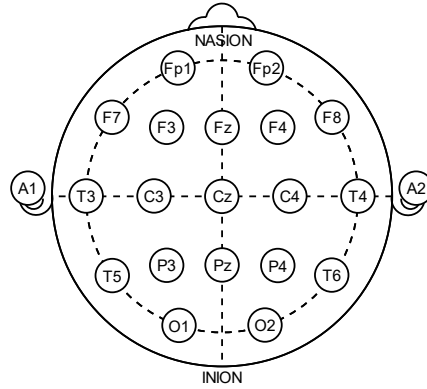


Figure 2 Locations of EEG channels - International 10-20 System (Wikipedia, 2019)

2.2. Experiment design and procedure

As a part of a larger study that investigates the effects of introductory information on driver's trust in automation and takeover performance, participants in our study were divided into two groups. Each group was shown an introductory video explaining the driver's role in each of the SAE levels of automation (SAE J3016, 2018), and a brief tutorial on operating the simulated ADS. The introduction video ended differently for the two groups, with one reminding the participants about their responsibility to ensure road safety and the other listing the benefits that might be achieved in the future with higher levels of automation. However, our study disregards this grouping as no statistically significant differences in takeover performance were found between the two groups (see Souders et al., 2021 for details).

Before the lab visit for the simulator experiments, participants completed an online survey that included a screening questionnaire (see Section 2.4 for the eligibility criteria), demographic information questions, and other behavioral/attitudinal questions (see Souders et al., 2021 for details). During the lab visit, participants signed an informed consent form and completed a practice run in the simulator that involved manually driving an automatic transmission vehicle in an urban environment with multiple intersections. This practice run also served as a screening procedure for participants with simulator sickness. Then, participants viewed the introduction video for their randomly assigned group. Neither the experimenter nor the participant knew about the assigned group (i.e., double-blind manipulation). Next, participants were equipped with a wearable eye-tracker (Dikablis Glasses 3; Ergoneers, 2018) and the EEG. Our study does not analyze eye-tracking data (see Agrawal and Peeta (2021) and Souders et al. (2021) for eye-tracking data analysis). Then, participants completed another practice run with the ADS and NDRT concurrently on a four-lane divided highway, to get acquainted with the ADS, its activation and deactivation procedures, and takeover warnings. In the practice run, drivers experienced both types of takeover warning multiple times, with a brief time of automated driving between two consecutive warnings, until they verbally confirmed that they are comfortable with handling the ADS. Traffic cones were used as obstacles to create safety-critical events that trigger the issuance of a takeover warning. In addition, each takeover warning in the practice run was preceded by a voice message (with a 5-second gap between the message and the warning) to prepare the participants and inform them about their expected response (i.e., pay attention to the road for an uncertainty alert, and take over manual control for a TOR).

Participants completed three experiment runs (approximately 10, 10, and 7 minutes, respectively) with moderate ambient traffic density (about 6-7 vehicles in a 500-meter radius). A break of about 5-10 minutes was provided between runs. Each run culminated in a safety-critical event that was preceded by takeover warning(s) (see Section 2.2.1 for details). Participants were asked to activate the ADS as soon as possible after the start of a run. They were allowed to take over manual control of the vehicle at any time if they are

concerned about road safety. However, they were informed that their final compensation for participation would depend on the number of correct responses to the NDRT, as well as road safety across all three runs. This was done to provide an incentive to disengage from driving and engage in the NDRT, which is expected in conditionally automated vehicles. Participants also completed a few surveys between runs (during breaks) and after the three runs that captured their trust in automation, perceived workload, and simulator sickness (see Souders et al., 2021 for details). Our study does not analyze data collected from these surveys. Finally, participants were debriefed and compensated for their participation. Although participants were informed that their amount of compensation depended on their performance in the NDRT and road safety, they received full compensation of \$45 regardless of their performance. The experiment protocol was approved by the Purdue University's Institutional Review Board (protocol #1811021326).

2.2.1. Safety-critical events

Each of the three experiment runs culminated in a different safety-critical event. The first and third runs present a non-mandatory takeover event with a delayed lateral and longitudinal response from the ADS, respectively. The second run presents a mandatory takeover event with an ADS failure. Since the larger study focuses on drivers' trust in automation, the order of the runs was not randomized to control participants' learning experiences. The safety-critical events used in this study are similar to those used by Körber et al. (2018). To ensure that there are no vehicles present during the takeover event other than the ego vehicle and the event vehicle(s), the ambient traffic was smoothly dissipated by changing the speed of ambient vehicles about 2000 meters before the takeover event. The details of each event are as follows.

In the first run, the event starts with the ego vehicle approaching a slower-moving bus (35 kph). An uncertainty alert is issued when the TTC is 6 seconds and, if there is no intervention from the driver within the next 4 seconds, the ego vehicle makes a close pass by shifting lane.

In the second run, the ego vehicle approaches a broken-down vehicle (0 kph) occluded by a slower-moving bus (35 kph). When the TTC with the broken-down vehicle is 8 seconds, the bus shifts lane, making the broken-down vehicle visible to the driver, and an uncertainty alert is issued. If the driver does not intervene by 4 seconds TTC, the ADS disengages and issues a TOR, thereby, making it mandatory for the driver to take over vehicle control to avoid a crash. After a TOR, the driver can prevent the crash by either braking (where applying the maximum deceleration rate of 12 m/s^2 after a response time of 2.78 seconds would just prevent the crash), switching to the left lane, or a combination of both.

In the third run, the ego vehicle approaches a slower-moving bus (55 kph), and an uncertainty alert is issued when the TTC is 7 seconds. If the driver does not intervene within the next 3 seconds, the ego vehicle starts to slow down and follows the bus at 55 kph until the end of the scenario or intervention from the driver.

2.3. Data preprocessing

Raw EEG signals are contaminated with low- and high- frequency noise known as artifacts. These artifacts can be generated due to physiological (e.g., eye or muscle movements) or non-physiological (e.g., presence of other electrical devices nearby) factors (Britton et al., 2016). The study experiment elicited head, eye, and muscle movements from a combination of driving (including responding to takeover warnings and resuming vehicle control) and NDRT. Participants were instructed not to speak during the experiment run to reduce unnecessary movements so as to mitigate artifacts. We used the B-Alert software's proprietary algorithm to remove the following artifacts from the raw EEG signals: electromyogram (muscle movements), eye blinks, excursions, amplifier saturations, and spikes (B-Alert, 2009). Then, the power spectral density of the EEG signal was computed by performing fast Fourier transformation over epochs of 1-second duration with 50% overlapping window. Next, EEG band powers were computed by averaging

the power spectral density in four frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz), and beta (13-30 Hz).

Since the magnitude of EEG band power varies across individuals, we standardized the band powers by computing Z-scores for each participant to estimate the relative changes in their neurophysiological indicators, and thereby, cognitive state. The Z-score of EEG band power for an individual i at epoch t in run r is computed using Eq. (1), where X represents the EEG band power, and $\bar{X}_i$ and SD_i are the mean and standard deviation of the EEG band power for individual i , respectively, over all three runs.

$$Z_{tri} = \frac{X_{tri} - \bar{X}_i}{SD_i} \quad (1)$$

We use the average Z-score of EEG powers (labeled the EEG average power) within a 5-second time window before the issuance of the uncertainty alert to assess the driver's pre-warning cognitive state.

2.4. Participants

We recruited participants from the Greater Lafayette community in Indiana, USA, through advertisements in Purdue University's weekly email newsletter, paper fliers at community events, and word of mouth. Participation eligibility criteria included: (i) being at least 18 years of age, (ii) having a valid driver's license, (iii) having no predisposition to motion sickness, (iv) having no mental or physical impairments (self-reported), and (v) if over the age of 64, passing an over-the-phone pre-screen memory impairment test (Wechsler Memory Scale; Wechsler, 1997). In addition, participants were also asked to avoid the consumption of any medication or caffeine for at least 8 hours prior to the experiment as this may affect EEG patterns (Blume, 2006; Pritchard et al., 1995), and thereby reduce EEG data quality. A total of 134 drivers participated in the study. However, we used data from only 118 participants for the analysis, because 16 participants were excluded due to having invalid EEG data in at least one of the runs. The invalid EEG data was due to two possible reasons: (i) EEG equipment malfunction resulting in missing data, and (ii) problems in synchronizing the EEG data with the driving data due to missing timestamps. Figure 3 shows the age distribution (29.44 ± 14.15 years) of the participants grouped by gender (55 males and 63 females).

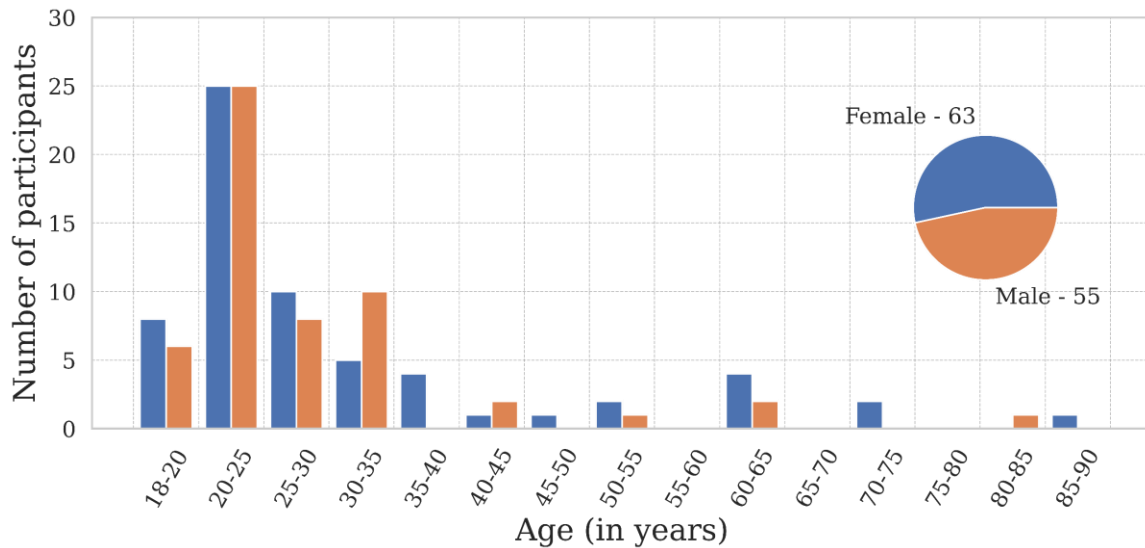


Figure 3 Age and gender distribution of the participants

3. Takeover Performance Index (TOPI)

This section presents the framework to compute the novel comprehensive takeover performance metric, Takeover Performance Index (TOPI), by combining multiple driving performance indicators representing three aspects of takeover performance: risk of collision, intensity of driver's response, and trajectory quality.

First, we define a takeover performance sub-index (T_i) for each driving performance indicator i on a unit interval (i.e., a value between 0 and 1) using a sigmoid function, given by Eq. (2). We choose the sigmoid function because: (i) it is bounded between the unit interval, and therefore, normalizes the driving performance indicators to a common dimensionless scale, and (ii) its S-shape diminishes the effects of extreme cases (outliers), thereby making T_i more robust.

$$T_i = \frac{1}{1 + e^{-W_i(x_i - c_i)}} \quad (2)$$

In Eq. (2), x_i is the value of the driving performance indicator i . c_i is the centering parameter that represents the indicator value at which T_i is equal to 0.5 (i.e., 50th percentile). W_i is the spreading parameter that controls the spread/curvature of the function. W_i can be back-calculated using Eq. (2) by substituting x_i with a reference value of driving performance indicator ($\tilde{x}_i$; spreading parameter reference) at a given T_i . In this study, we use $\tilde{x}_i$ at the 75th percentile of T_i (i.e., T_i equal to 0.75). Figure 4 illustrates the distribution of T_i for three different spreading parameters. The parameter values can be determined by using insights from the literature or by making reasonable assumptions in the context of the takeover event, as illustrated later in this section. For example, a smaller spread of deceleration rate may be preferred in congested traffic conditions to avoid rear-end collisions, while a larger spread may be acceptable in uncongested traffic. This mechanism enables the TOPI to adapt to different takeover situations by allowing the selection of appropriate driving performance indicators and their parameter values.

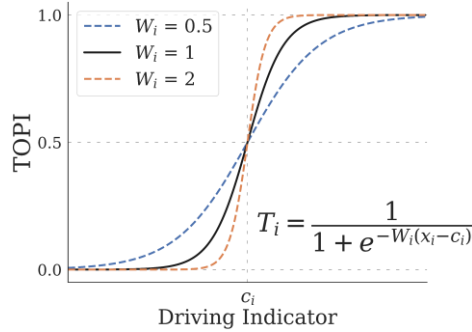


Figure 4 Sigmoid function

Next, we compute the TOPI value (T) by taking the geometric mean of takeover performance sub-indices for all driving performance indicators, as shown in Eq. (3). Since takeover performance sub-indices are defined on a unit interval, their geometric mean TOPI varies between 0 and 1, with a higher value of TOPI value representing a better takeover performance. Geometric mean is chosen over arithmetic mean as it is lower than the arithmetic mean, which implies that poor takeover performance sub-index (i.e., values closer to 0) of a single driving performance indicator will have a larger effect on the TOPI value. For example, a higher value of deceleration rate (typically representing a poor takeover performance), with a sub-index value closer to 0, can result in a longer minimum TTC (typically representing a good takeover performance), with a sub-index value closer to 1. However, their resulting TOPI value (geometric mean)

will be closer to 0, indicating a poor takeover performance. Hence, by computing sub-indices of driving performance indicators using a non-linear (sigmoid) function and by combining them using the geometric mean, the TOPI partly captures the interdependencies between these indicators. Further, the TOPI provides a conservative estimate of takeover performance, which is suitable, and even preferred, for safety-critical situations. Therefore, the TOPI captures multiple aspects of takeover performance in a single, comprehensive metric, and thereby, is suitable to benchmark the effects of driver's pre-warning cognitive state on the overall takeover performance.

$$T = \sqrt[n]{\prod_i^n T_i} \quad (3)$$

In this study, we use four driving performance indicators to represent the three aspects of takeover performance. The risk of collision is represented by minimum TTC, where a longer minimum TTC indicates a lower risk of collision, and thereby, a better takeover performance. The intensity of driver's response is represented by maximum deceleration rate and maximum steering wheel angle, both of which are negatively correlated with the takeover performance. Trajectory quality has two aspects: longitudinal and lateral. However, the longitudinal trajectory quality is correlated with the risk of collision and is captured by minimum TTC. To assess the lateral trajectory quality, we define a new driving performance indicator, maximum lateral trajectory deviation (LTD), which is defined as the maximum lateral deviation from the ideal lateral trajectory in the context of a takeover event. In the takeover events designed in this study, the ego lane of the driver is blocked either by a slower-moving bus or by a broken-down vehicle. Thus, ideally, the driver first needs to maneuver the vehicle to the center of the adjacent lane (i.e., the target lane), and then, return to the center of the ego lane after passing the blocking vehicle. The maximum LTD is computed as the sum of the two maximum lateral deviations corresponding to these two maneuvers, as given by Eq. (4). The first component in Eq. (4) is the maximum lateral deviation from the center of the target lane (ΔL_{target}) when the vehicle is moving to the target lane, as illustrated in Figure 5. It captures the maximum lateral deviation due to: (i) lateral undershoot, which happens when the vehicle does not reach the center of the target lane, and thereby, has an increased risk of a side collision with the blocking vehicle, and (ii) lateral overshoot, which happens when the vehicle goes past the center of the target lane and has an increased risk of going off the road. The second component in the Eq. (4) is the maximum lateral deviation from the center of the ego lane (ΔL_{ego}) due to overshooting in the other direction when the driver is returning to the ego lane after passing the blocking vehicle, as illustrated in Figure 5.

$$\text{LTD} = \Delta L_{\text{ego}} + \Delta L_{\text{target}} \quad (4)$$

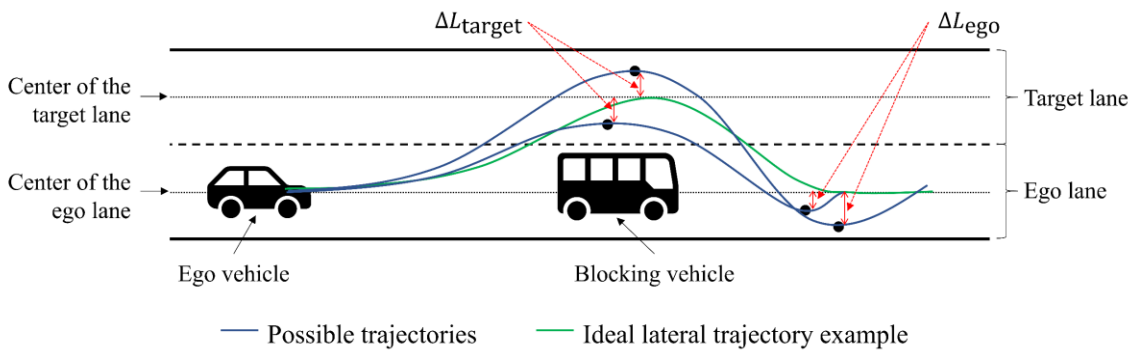


Figure 5 Components of maximum lateral trajectory deviation

The parameter values to compute the individual takeover performance sub-index for each of the four driving performance indicators are determined as follows. For minimum TTC, Minderhoud and Bovy (2001) discussed that while the TTC of 3 seconds may be optimal (i.e., least false alarms) for collision warning systems, advanced driver assistance systems can implement even lower TTC values (e.g., 2 seconds). We use 2.5 seconds and 1 second as c_i and $\tilde{x}_i$, respectively, for minimum TTC. McGee et al. (2012) reported that most handbooks recommend deceleration rates between 3 m/s² and 4.5 m/s² for designing traffic signals, with 3.4 m/s² considered as a comfortable deceleration rate. Thus, to assess the intensity of the driver's response, we assume the values of c_i and $\tilde{x}_i$ for maximum deceleration rate to be 4.5 m/s² and -2 m/s², respectively. The negative spreading parameter value means that higher values of the driving performance indicator lead to a lower TOPI value. We did not find recommended estimates for the maximum steering wheel angle in the literature, as it is highly situation-dependent. Thus, we assume c_i and $\tilde{x}_i$ for maximum steering wheel angle to be 40 degrees and -10 degrees, respectively. These estimates are based on the visual inspection of the maximum steering wheel angle in runs with smooth takeover performance (based on the authors' subjective assessment) and its overall distribution in the study data. Likewise, for maximum LTD, we assume c_i and $\tilde{x}_i$ as one-fourth and negative one-eighth of the lane width, respectively. The lane width in the simulated driving environment is 3.66 meters. The parameters values used in this study are shown in Table 1. It should be noted that these parameter values are specific to the takeover situations in this study, including the road and traffic environment and the setup of safety-critical events. However, the proposed TOPI framework is flexible and can be adapted to different takeover situations by choosing appropriate driving performance indicators and their parameter values. Appendix I presents the mean, standard deviation, median, and quantiles of the driving performance indicators used to calculate the TOPI for the study data.

Table 1 Parameter values for computing takeover performance index

Driving performance indicator	Centering (c_i)	Spreading parameter reference ($\tilde{x}_i$)
Minimum TTC	2.5 seconds	1 second
Maximum deceleration rate	4.5 m/s ²	-2 m/s ²
Maximum steering wheel angle	40 degrees	-10 degrees
Maximum lateral road deviation	0.915 m	-0.457 m

In our study, the driving performance indicators are computed using driving data within a 15-second time window after the issuance of the uncertainty alert to evaluate takeover performance. The TOPI is not calculated for runs where the ADS was not disengaged (either from driver intervention or after a TOR; 41 runs) or the participant intervened before an uncertainty alert was issued (7 runs). The TOPIs for 19 runs were excluded due to an unexpected error (a rogue vehicle appearing in front of the ego vehicle) during the takeover event. Based on these observations, we calculated the TOPI for 287 runs across 118 participants. The mean value and the standard deviation of the TOPI for the study sample are 0.457 and 0.227, respectively. Figure 6 illustrates the distribution of the TOPI for all participants. The zero-inflated TOPI is due to the poor takeover performance by several participants, especially in their first run.

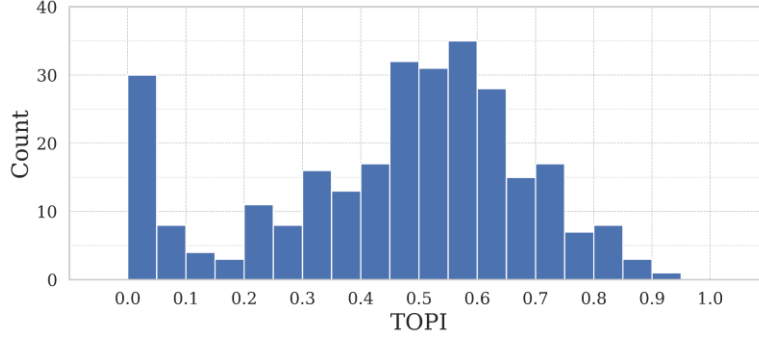


Figure 6 Distribution of takeover performance index

3.1. Comparison with existing takeover performance metrics

In this section, we compare the proposed TOPI with the integrative take-over performance score (TOPS) proposed by Radlmayr et al. (2018). As discussed in Section 1.2, TOPS includes three dimensionless parameters that relate to vehicle guidance, mental processing, and selective rating parameter. Since the TOPI is calculated based on driving performance indicators related to vehicle guidance, we compare the vehicle guidance parameter (VGP) of TOPS and the TOPI. The VGP is calculated using the equation below.

$$VGP = (1 - vgp_{crash}) \times \left(\frac{vgp_{ttc} + vgp_{long} + 2 \times vgp_{lat}}{4} \right) \quad (5)$$

In Eq. (5), vgp_{crash} is the binary indicator for crash (0 = “no crash”, 1 = “crash”). vgp_{ttc} is the minimum TTC standardized by dividing the time budget (see Section 2.2.1), with values greater than 1 set to 1. vgp_{long} and vgp_{lat} are the maximum magnitude of longitudinal and lateral accelerations, respectively, both standardized by dividing by the maximum acceleration and then subtracting from 1. There are two adjustments made to VGP as calculated by Radlmayr et al. (2018). First, they proposed the maximum acceleration to be 10 m/s²; however, our simulated vehicle could attain maximum acceleration of 12 m/s². Thus, we use 12 m/s² instead of 10 m/s² to standardize vgp_{long} and vgp_{lat} . Second, they multiplied vgp_{crash} with other components directly, instead of multiplying $(1 - vgp_{crash})$ (Radlmayr et al., 2018, Eq. (1)). We made this correction as they stated that the vgp_{crash} is multiplied to obtain a VGP of 0 in case of a crash, which means that the multiplication term should be 0 in case of a crash.

Figure 7 presents the comparison between the calculated TOPI and TOPS values for the 287 experiment runs. The figure shows that the TOPI value is significantly lower (closer to 0) than the TOPS value for several runs. Unlike the TOPS that uses weighted arithmetic mean, the TOPI uses the geometric mean to combine different driving performance indicators, which heavily penalizes any lower indicator values. This property makes the TOPI more conservative and, thereby, desirable to estimate takeover performance in safety-critical situations. In addition, the TOPS distribution is more skewed towards the higher values compared to the TOPI distribution. This is because the TOPI uses optimal values of driving performance indicators to standardize the variables using a sigmoid function. In contrast, the TOPS uses extreme values (e.g., physical limit of acceleration) or initial values (e.g., time budget) of these indicators. This makes the TOPI suitable for benchmarking takeover performance, unlike the TOPS which represents differences in takeover performances and not necessarily their quality, as acknowledge by Radlmayr et al. (2018).

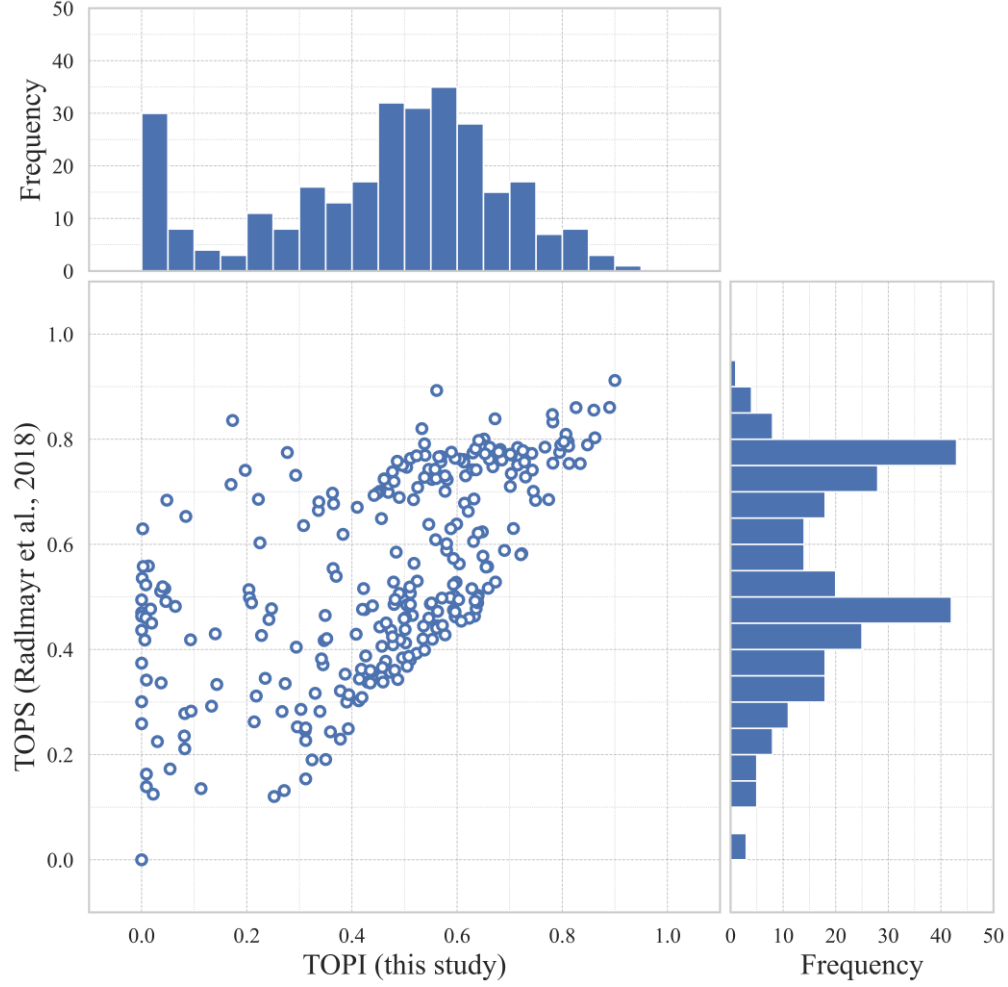


Figure 7 Comparison of the proposed TOPI with the TOPS from Radlmayr et al. (2018)

4. Data Analysis

As stated earlier, the study investigates the impacts of driver's pre-warning cognitive state on takeover performance using physiological indicators (EEG average powers). We draw insights from the neuroscience literature to link EEG average powers in different EEG bands and different regions of the brains with specific aspects of driver cognition. Thus, we use EEG average powers as indicators of driver's pre-warning cognitive state to analyze its effects on takeover performance. We also examine the effects of driver attributes such as age and driver experience, and their interaction effects, with driver's pre-warning cognitive state on takeover performance. In addition, we analyze the effects of additional factors, including novelty in takeover experience and type of takeover warning, that may affect takeover performance. Due to the shortcomings of existing takeover performance measures (as discussed in Section 1.2), we propose a TOPI that provides a comprehensive metric that is suitable to benchmark the effects of driver's pre-warning cognitive state (using EEG average powers), driver attributes, and other factors on takeover performance.

We estimate linear mixed models (LMMs) to analyze the effects of the aforementioned factors on the TOPI. There are two key benefits of using LMM: (i) it accounts for the non-independent or correlated errors that arise due to panel data (multiple runs from the same participant), and (ii) unlike Analysis of Variance (ANOVA), it is robust to missing data and can provide unbiased results without the need for listwise

deletion (i.e., deleting entire data for a participant if a single data point is missing). Therefore, it enables us to use data for participants who did not take over manual control of the vehicle (i.e., TOPI is not calculated) in all three runs.

In this study, we estimate 76 LMMs for each of the four EEG bands and nineteen EEG channels independently. The basic form of estimated LMMs is given by Eq. (6).

$$T^2 = \beta_0 + \beta_{nov} + \beta_{TOR} + \beta_{EEG} + \beta_{age} + \beta_{exp} + \beta_{EEG*age} + \beta_{EEG*exp} + \gamma + \varepsilon \quad (6)$$

where T^2 denotes the square of TOPI and is the dependent variable, and β_0 is the model intercept. We transform (squared) TOPI to meet the model assumption of normality of residuals. The main effects of the novelty in takeover experience (indicator variable for the first run) and the indicator variable for the presence of TOR are represented by β_{nov} and β_{TOR} , respectively. β_{EEG} , β_{age} , and β_{exp} denote the main effects of EEG average power, driver's age, and driving experience, respectively, and $\beta_{EEG*age}$ and $\beta_{EEG*exp}$ denote their corresponding interaction effects. γ is the random effects coefficient for the panel data from multiple experiment runs for the same participant, and ε is the normally distributed error term.

Driver's age is treated as a continuous variable while driving experience is defined as an indicator variable. Participants having a driver's license for more than 5 years are considered as experienced drivers and their counterparts as novice drivers. Although there is a natural correlation between age and driving experience, the data show a good mix of age and driving experience among drivers between 20 to 35 years of age, as shown in Figure 8.

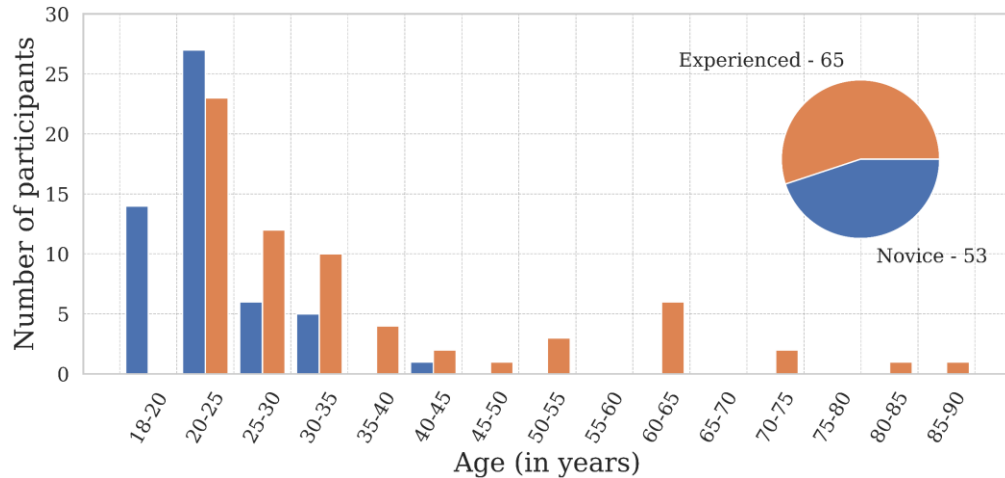


Figure 8 Age and driving experience distribution of the participants

We assess the relative goodness-of-fit of the LMMs of the TOPI by comparing its Akaike Information Criterion (AIC) with the AIC of the null model (i.e., a linear mixed model with intercept and random effects only), which is given by Eq. (7). A lower AIC value indicates a better goodness-of-fit. We also test the assumption of normality of the model residuals using the Shapiro-Wilk test, which tests the null hypothesis that the sample is normally distributed. We use the significance level (p-value) of 0.05 to reject the null hypothesis of the Shapiro-Wilk test.

$$T^2 = \beta_0 + \gamma + \varepsilon \quad (7)$$

5. Results

5.1. Descriptive results

We observed one crash in each of the three runs (by three different participants) during the safety-critical event after the issuance of an uncertainty alert. In comparison, a previous study with a two-level takeover warning system similar to the one used in this study observed no crash (in 76 trials) when a TOR was preceded by an uncertainty alert (or monitoring request), one crash (in 74 trials) when only a TOR was issued, and three crashes (in 38 trials) when an uncertainty alert was provided without a TOR in a mandatory takeover situation (Lu et al., 2019). The TOPI was calculated as 0 for the runs with a crash. In addition, participants did not disengage the ADS in 41 runs or intervened before an uncertainty alert was issued in 7 runs out of 354 runs (based on three runs each for 118 participants). As noted in section 3, these runs were excluded from the analysis.

Previous studies have reported a continuous (linear or logarithmic) positive trend in driver's takeover performance over successive experiment runs due to learning effects (Gold et al., 2018; Happee et al., 2017). However, our preliminary data analysis indicates a strong positive stepwise trend instead of a continuous trend in takeover performance due to learning effects after the driver's first experience with a takeover situation (i.e., novelty effects), as illustrated in Figure 9. Understanding the learning/novelty effects in takeover performance can provide insights to policymakers for developing operator training programs and driver licensing strategies for conditionally automated vehicles. The preliminary data analysis also shows a lower TOPI value in the presence of a TOR in the second run. These results can aid auto manufacturers to design takeover warning systems that improve takeover performance, as from their perspective poor takeover performance will not only reduce road safety, but will also negatively impact drivers' user experience with and trust in the ADS.

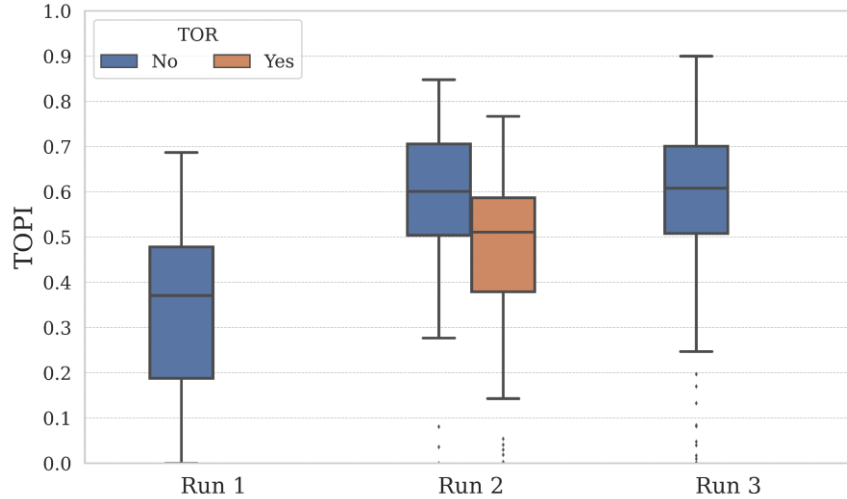


Figure 9 Boxplot of takeover performance index across runs and TOR

5.2. Model preliminaries

The estimation results for all 76 LMMs (4 EEG bands and 19 EEG channels) of the TOPI are presented in Table 2. Results show that all 76 LMMs have a relatively better goodness-of-fit compared to the null model; the estimated AICs for all the LMMs are lower than that of the null model. The assumption of normality of residuals is satisfied (at 0.05 significance level) for all estimated LMMs of the TOPI with p-values greater than 0.05 for the Shapiro-Wilk test. The model intercepts (β_0) for all estimated LMMs of the

TOPI are found to be statistically significant ($p < 0.01$) with a mean value of 0.412. The random effects (γ) variance is positive across all LMMs of the TOPI.

A heatmap-based visualization of the coefficients for all 76 estimated LMMs of the TOPI is presented in Figure 10. For a given LMM of the TOPI (i.e., specific EEG channel and EEG band), the value of a coefficient is presented at its corresponding coefficient row, EEG band column, and EEG channel location (refer to Figure 2). The red color indicates a positive coefficient value, while the blue color indicates a negative coefficient value. The statistical significance levels of 0.01 (significant) and 0.05 (marginally significant) are shown as solid black circles and hollow circles, respectively.

Table 2 Summary of estimation results of the LMMs of the TOPI for all EEG channels and EEG bands

Measures for LMMs estimating the TOPI	Mean	Minimum	Maximum	Null model
Intercept (β_0)	0.4123	0.3859	0.4329	0.2604
Coefficient of age (β_{age})	-0.0014	-0.0025	-0.0003	-
Coefficient of driving experience (β_{exp})	-0.0048	-0.0334	-0.0186	-
Coefficient of EEG average power (β_{EEG})	-0.0026	-0.0362	0.0402	-
Coefficient of interaction between EEG average power and age ($\beta_{EEG*age}$)	-0.0010	-0.0034	0.0008	-
Coefficient of interaction between EEG average power and driving experience ($\beta_{EEG*exp}$)	-0.0402	-0.0042	0.0808	-
Coefficient of novelty effect (β_{nov})	-0.2182	-0.2211	-0.2156	-
Coefficient of TOR presence (β_{TOR})	-0.1100	-0.1154	-0.1033	-
Random effects variance (γ)	0.2199	0.1661	0.2723	0.0289
Akaike Information Criterion (AIC)	-227.7487	-237.3216	-222.9247	-140.1958
Shapiro-Wilk test p-values	0.1134	0.0548	0.2545	0.0000

5.3. Effects of age

The mean coefficient of age (β_{age}) for all estimated LMMs of the TOPI is -0.0014. Although the main effect of age is only marginally significant ($p < 0.05$) in some of the estimated LMMs, overall, it indicates a decrease in the TOPI value with age. These results are somewhat inconsistent with the findings from a previous study by Gold et al. (2018), which reported a linear increase in minimum TTC with age. However, unlike the TOPI, their analysis did not consider the intensity of the driver's response, and thus, only partially explains the impacts of age on the overall takeover performance. Körber et al. (2016) reported significantly higher minimum TTC for older drivers, but marginally stronger brake reactions, which have counteracting effects on the proposed TOPI. They also argued that even though the expected cognitive decline suggests an increase in reaction times with increasing age, years of experience with driving and resulting expertise may have affected the task performance in a naturalistic driving task. Our study addresses these concerns by explicitly analyzing the impacts of driving experience (a proxy for task expertise) and driver cognition, as discussed hereafter.

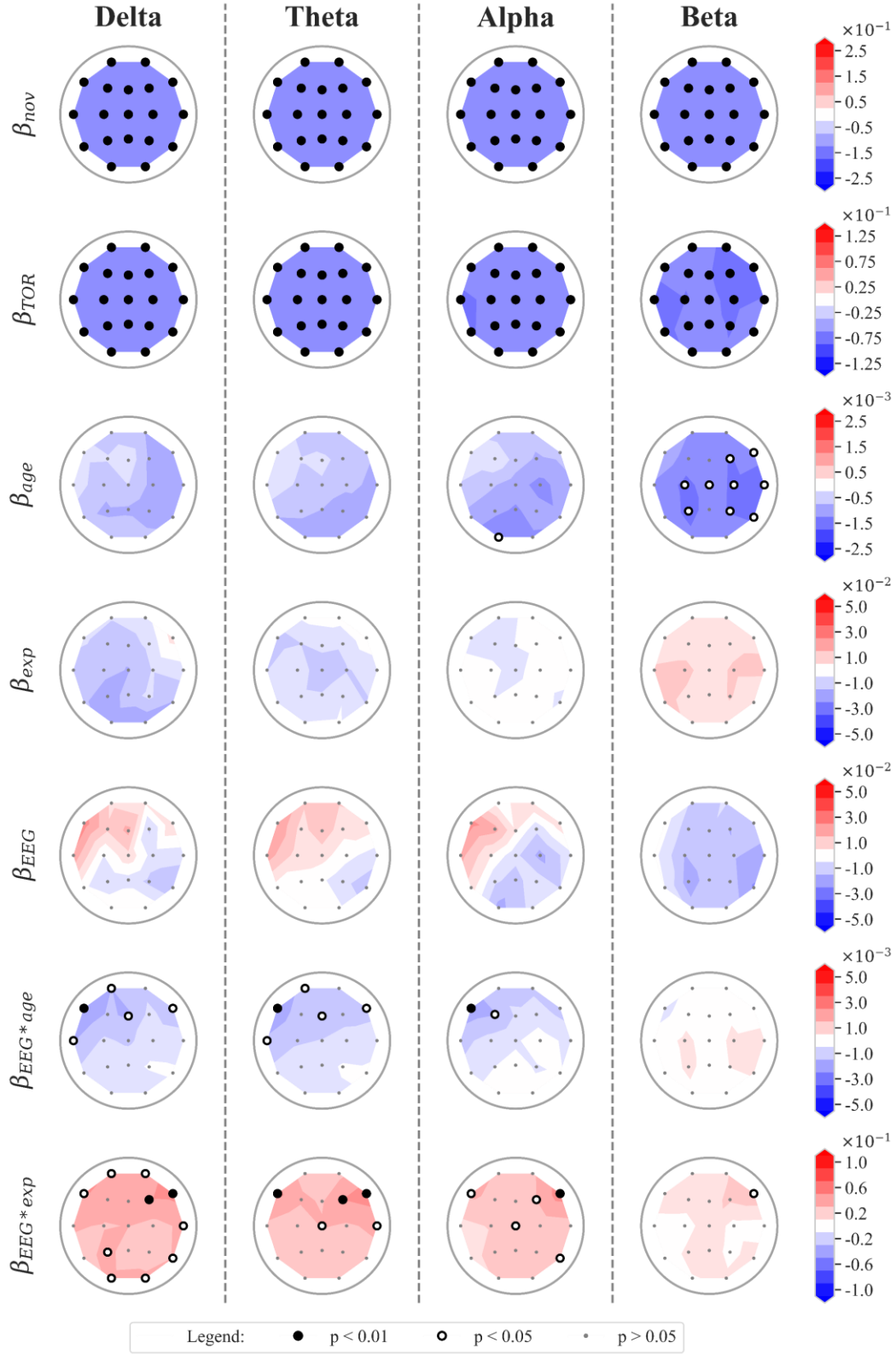


Figure 10 Results of the seventy-six LMMs of the TOPI for nineteen EEG channels and four EEG bands. Each dot illustrates the coefficient of a specific variable (row) for a LMM for a specific EEG

channel (as shown in Figure 2) and EEG band (column). Solid black circles and hollow circles represent the level of significance of the coefficient.

5.4. Effects of driving experience

The coefficients of driving experience (β_{exp}) are found to be statistically non-significant for all the estimated LMMs of the TOPI with a mean value of -0.005. There is limited research on explicitly modeling the impacts of driving experience on the TOPI, as most studies discuss it indirectly as a covariate of age. Our results indicate that driving experience with human-driven vehicles did not have significant primary effects on takeover performance in conditionally automated vehicles. However, we did find their significant interaction effects with driver's pre-warning cognitive state, as discussed in Section 5.5.3.

5.5. Effects of driver's pre-warning cognitive state

5.5.1. Main effects

The main effects of EEG average power (β_{EEG}) on the TOPI are found to be statistically non-significant for all EEG channels and across all EEG bands, as illustrated in Figure 10. Two key insights can be drawn from these results. First, we infer driver's pre-warning cognitive state directly from EEG average powers, and thereby, the non-significant values of β_{EEG} indicate that driver's pre-warning cognitive state did not have significant primary effects on the TOPI. Second, since the TOPI provides a single, comprehensive metric to capture the overall driving performance during a takeover event, the results indicate that drivers' pre-warning cognitive state may not directly affect the overall takeover performance. However, the overall effects of pre-warning cognitive state, including its interaction effects with age and driving experience, on the TOPI are found to be statistically significant, as discussed next.

5.5.2. Interaction effects with age

The coefficients of interaction between EEG average power and age ($\beta_{EEG*age}$) are mostly negative for the estimated LMMs of the TOPI, as illustrated in Figure 10. They are statistically significant or marginally significant for the delta, theta, and alpha bands in the left frontal and temporal lobes. These results suggest that certain cognitive states that are manifested as higher delta, theta, and alpha band powers primarily in the frontotemporal cortex have significantly higher negative impacts on the TOPI with increasing age. In the driving context, existing literature has linked higher delta band power in the frontal lobe (Jap et al., 2009; Morales et al., 2017) and higher theta band power in frontal, temporal, and in other regions of the brain (Jap et al., 2009; Shamsul et al., 2014) with mental fatigue induced by long monotonous driving. Similarly, Lal et al. (2003) reported an overall increase in delta, theta, and alpha activities with an increase in driver fatigue. In a non-driving context, Harmony (2013) reported higher delta band power in frontal and centroparietal regions of the brain while performing tasks that require increased attention to internal processing (e.g., mental calculation) or memory retrieval (e.g., semantic task). Aftanas and Golocheikine (2001) associated higher theta but lower alpha band powers in the frontal cortex with the states of internalized attention or positive emotional states. Abhang et al. (2016) associated higher theta band power with an increase in inward focus, drowsiness, or deeply relaxed state, and higher alpha band power with a state of passive attention. Thus, the TOPI value for drivers significantly decreases with age when they are in a relative state of fatigue, drowsiness, passive attention, or low alertness level. In addition, the NDRT implemented in this study does not require mental calculation or memory retrieval and was considered to be "monotonous and boring" by most participants, which could have contributed to inducing these cognitive states.

5.5.3. Interaction effects with driving experience

In contrast to the interaction effects of age, the coefficients of interaction between EEG average power and driving experience ($\beta_{EEG*exp}$) are mostly positive. The coefficients are statistically significant or marginally significant in several regions of the brain for the delta band and in the frontal and temporal lobes for the theta and alpha bands, as illustrated in Figure 10. These results show that experienced drivers have a better TOPI value compared to novice drivers in a state of fatigue, drowsiness, passive attention, or low alertness level. Given our sample characteristics (see Figure 8), this illustrates a counteracting effect of age and experience, especially for middle-aged drivers, where the former results in cognitive decline while the latter improves the anticipation of and response towards unexpected events. Further, a higher delta band power in the parietal cortex has been associated with performing visually complex tasks compared to mentally complex tasks (Wilson, 2002). Thus, the marginally significant delta power in this region suggests that engaging in visually distracting NDRTs could have an adverse effect on the takeover performance of novice drivers.

5.6. Effects of novelty in takeover experience

The coefficients of novelty effect (β_{nov}) are found to be statistically significant ($p < 0.01$) for all the estimated LMMs of the TOPI, as illustrated in Figure 10, with their mean value equal to -0.218. These results indicate that participants performed poorly (i.e., a lower TOPI value) in their first realistic takeover situation, even with a hands-on practice session with the ADS, compared to future events. These findings suggest that a simplified or non-critical takeover practice may not be sufficient to prepare drivers for real-world takeover situations. Further, the driving duration and takeover event details were varied in each run, with the aim of reducing the expectation of the takeover event in future runs. The stepwise novelty effect on the TOPI found in this study is partly comparable to the positive logarithmic effect of repetition on minimum TTC found by Gold et al. (2018).

5.7. Effects of type of takeover warning

The coefficients of TOR presence (β_{TOR}) are found to be statistically significant ($p < 0.01$) for all estimated LMMs of the TOPI, with a mean value of -0.110. The negative coefficient indicates a lower TOPI value if a TOR is issued in the second run. This could be because a TOR is issued with a 4-second time budget compared to an 8-second time budget for an uncertainty alert, which may stimulate a sense of urgency and elicit an intense response from the driver resulting in a poor TOPI value.

6. Discussion

The results show marginally significant main effects of age, but no statistically significant main effects of driving experience on the TOPI. They indicate a decrease in the TOPI value with age, most likely due to an age-related decline in reaction time and quality. Previous studies reported that older adults performed better on certain driving performance indicators (e.g., minimum TTC) (Gold et al., 2018) but worse on others (e.g., maximum deceleration and takeover time) (Körber et al., 2016; Li et al., 2018), which makes it difficult to assess their overall takeover performance. Since the TOPI integrates multiple driving performance indicators, this study provides a more comprehensive understanding of the effects of age on the overall takeover performance. Körber et al. (2016) reasoned that older adults' better takeover performance (based on minimum TTC) is probably due to their greater driving experience. However, the lack of significant main effects of driving experience on the TOPI found in our study suggests that experience with human-driven vehicles does not directly entail a better takeover performance in conditionally automated vehicles. It does, however, benefit drivers in responding to takeover situations under certain driver's pre-warning cognitive states, as discussed hereafter. In addition, although the direct

effects of the driver's pre-warning cognitive state were found to be statistically non-significant, its interaction effects with individual characteristics (i.e., age and driving experience) were found to be statistically significant. While certain cognitive states such as fatigue, drowsiness, passive attention, and low alertness had significantly worse impacts on takeover performance of older drivers compared to younger drivers, experienced drivers performed better under such cognitive states compared to novice drivers. Since age and driving experience are typically correlated, this provides a viable explanation for the widely varying results related to the effects of age on takeover performance in the existing literature (Zhang et al., 2019). The results also suggest that experienced drivers can potentially have a better TOPI value compared to novice drivers while engaged in a visually distracting NDRT. This could be because of the differences in how experienced and novice drivers interact with an NDRT. He and Donmez (2019) reported that experienced drivers have shorter glance durations towards an NDRT and spend less time interacting with it than novice drivers under partial automation. These differences in the impacts of NDRT-induced distraction on takeover performance between drivers with varying driving experience highlight that a simple, one-size-fits-all approach may not work in designing regulations for using conditionally automated vehicles. A uniform regulation may be too restrictive and reduces the potential benefits of these vehicles to several drivers, or it may overestimate the abilities of some drivers to respond to critical takeover situations that may pose a risk to road safety. Policymakers and regulatory agencies can use these insights to identify the most vulnerable subgroups of the population based on driver attributes during the transitional period towards higher levels of automation, and develop focused operator training programs and driver licensing strategies that make the transition smoother and safer. The study insights can also aid them to incorporate the interactions between driver attributes and cognitive aspects of using NDRT while devising policies that regulate the use of conditionally automated vehicles.

Past studies have reported significant effects of type of takeover situation on takeover performance (Dogan et al., 2019; Radlmayr et al., 2014), primarily when drivers need to react differently (e.g., switch to the right lane instead of the left lane) to the takeover situation. In this study, the ambient traffic conditions during the safety-critical events (i.e., no traffic) and the expected driver reactions to prevent a crash under an intervention (i.e., decelerate, shift to the left lane, or a combination of both) are same across all three runs. Although the different safety-critical events (i.e., type of takeover situation) may influence the TOPI, our experiment setup reduces this influence and enables us to investigate the effects of novelty in takeover experience and type of takeover warning. In this study, we found that driver's takeover performance improved significantly in the latter experiment runs after experiencing a realistic takeover situation in the first run (i.e., stepwise trend), which is different from the continuous positive trend reported by previous studies on individual driving performance indicators of takeover performance (Gold et al., 2018; Happee et al., 2017). This suggests that practicing taking over vehicle control in a simplified environment (practice run) did not help the drivers much. The novelty of experiencing a takeover situation can have a significantly worse impact in real-world driving situations compared to simulated driving as conditions can be more complex and uncertain in nature. These results have important implications for policymakers to develop operator training programs and driver licensing strategies for conditionally automated vehicles as traditional methods may fall short when preparing the public for operating these vehicles. However, since the experiment runs were not randomized in this study, the observed differences in takeover performance could also be caused by scenario-specific factors (i.e., type of takeover situation). Hence, more research is needed to support the novelty of experiencing a takeover situation.

The effects of type of takeover warning suggest that waiting for a TOR in a graded warning system rather than taking over vehicle control after an uncertainty alert can result in significantly worse takeover performance. Similar results were reported by Eppele et al. (2018) in a two-step warning system (similar to ours) using minimum TTC and maximum steering wheel angle as performance indicators. This shows that

the drivers who followed the system instructions faced a more dangerous situation compared to their counterparts. Such experiences can reduce drivers' trust in automated vehicles (i.e., resuming manual control of the vehicle when it is not required) (Hergeth et al., 2015; Körber et al., 2018), which can consequently lead to underutilization of the system (Choi and Ji, 2015). In this study, most drivers took over manual control of the vehicle even when it was not required and the ADS would have safely handled the situation (like in the first and third runs). Moreover, drivers exhibited poor takeover performance and potentially compromised road safety in several of these non-mandatory takeover events, as shown in Figure 9. This highlights the importance of fostering trust in the system through demonstrated system reliability and by educating drivers about the ADS capabilities. Although this study did not compare the impacts of issuing a TOR that is not preceded by an uncertainty alert or the effects of different time budgets for TOR on takeover performance, it illustrates the influence of takeover warning system design on driver behavior and performance in conditionally automated vehicles. This has key implications for auto manufacturers and ADS designers as automated vehicle technologies are introduced in the market, especially related to road safety and trust/adaptability with these systems.

7. Concluding Comments

This study estimates driver's pre-warning cognitive state using EEG data collected in driving simulator experiments and evaluates its impacts on takeover performance. Although using EEG is currently impractical in the operational context, it allows for a detailed cognitive analysis that can provide valuable insights for the design and planning of ADS and takeover warning systems in conditionally automated vehicles. It also enables policymakers to incorporate drivers' cognitive aspects in devising regulatory strategies for using these vehicles.

Benchmarking the effects of driver's pre-warning cognitive state on takeover performance requires a comprehensive metric that captures multiple aspects of takeover performance. However, existing takeover performance metrics are inadequate in their ability to capture the interdependencies between different driving performance indicators, and to provide a single metric for the overall takeover performance. To address this key gap in the literature, we propose a novel framework to compute a comprehensive takeover performance metric, TOPI, that combines multiple driving performance indicators representing different aspects of takeover performance. The proposed framework is flexible and can be adapted to different takeover situations by selecting appropriate driving performance indicators. By proposing a single metric to quantify takeover performance, this study advocates for standardization in measuring takeover performance, which would provide a consistent and comprehensive measure to different stakeholders (e.g., auto manufacturers, regulatory agencies) for assessing takeover performance.

The study results show that takeover performance decreases with age but increases with experience when the driver is relatively fatigued, drowsy, or has a low level of alertness. This is interesting as age and driving experience are typically positively correlated, and these results show the counteracting effects of possible cognitive decline due to age and better response quality under unexpected situations due to experience. Thus, they also illustrate the importance of considering driver's pre-warning cognitive state in modeling takeover performance. The results also highlight the effects of novelty in takeover experience and type of takeover warning on takeover performance. The study findings provide valuable insights to design operating and licensing strategies, takeover warnings, and regulations for conditionally automated vehicles, as discussed in the previous section.

The study can be extended in the following ways. First, we did not control for the order effects of experiment runs. Controlling these effects in future experiments may provide better insights regarding the impacts of driver's pre-warning cognitive state on takeover performance. Second, the current analysis does

not include participants who took over vehicle control before the issuance of a takeover warning. Future research can develop mechanisms to continuously analyze driver's cognitive states to investigate whether these participants were more attentive due to their greater cognitive abilities or due to the lack of trust in the ADS. Third, although having a sample comprising of mainly younger adults enables us to better understand the effects of age and driving experience, future studies can include a more representative sample of the general population to improve the generalizability of the results.

Potential future research directions are as follows. First, the proposed takeover performance metric can be tested in different takeover situations. It can also be validated, and subsequently calibrated, using expert rater assessment. Second, future studies can assess the feasibility of physiological indicators (e.g., eye-tracking and heart-related measurements) that can be measured using in-vehicle driver monitoring systems to evaluate takeover performance. Third, it is important to examine the effects of the modality of takeover warning (e.g., a combination of a visual and auditory warnings) as varying modes or combinations thereof may elicit different responses from drivers based on their pre-warning cognitive state. Fourth, investigating the effects of different NDRTs on driver's pre-warning cognitive state and on takeover performance may provide insights to policymakers to design NDRT-related regulations in conditionally automated vehicles.

CRedit authorship contribution statement

Shubham Agrawal: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Project administration, Visualization, Writing - original draft. **Srinivas Peeta:** Conceptualization, Methodology, Project administration, Writing - review & editing, Resources, Supervision, Funding acquisition.

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1 Appendix I: Data distribution for the TOPI parameters grouped by runs

Driving performance indicator	Run	Mean	Std. Dev.	25% quantile	Median	75% quantile
Minimum TTC (seconds)	1	2.25	0.92	1.68	2.19	2.84
	2	1.92	0.84	1.28	1.80	2.50
	3	8.91	23.72	3.41	4.04	5.48
	All	3.99	12.90	1.65	2.50	3.46
Maximum deceleration rate (m/s ²)	1	6.92	2.24	5.79	7.26	8.15
	2	3.22	2.90	0.99	1.61	5.36
	3	4.79	2.36	2.68	4.78	6.54
	All	4.90	2.98	1.70	5.40	7.15
Maximum steering wheel angle (degrees)	1	50.68	63.39	14.77	26.90	52.77
	2	25.94	44.20	8.82	14.52	24.57
	3	27.47	33.33	10.14	16.67	26.99
	All	34.65	50.20	10.43	18.28	32.03
Maximum lateral road deviation (meters)	1	1.54	1.81	0.48	0.86	1.81
	2	0.95	0.85	0.49	0.78	1.14
	3	1.14	1.20	0.47	0.72	1.27
	All	1.20	1.35	0.48	0.77	1.28

2