

Evaluating the Cognitive and Psychological Effects of Real-Time Auditory Travel Information on Drivers using EEG

Shubham Agrawal

Department of Sociology, Anthropology and Criminal Justice
Clemson University, Clemson, SC 29634, USA

Email: agrawa3@clemson.edu

ORCID: <https://orcid.org/0000-0002-0990-9785>

Srinivas Peeta

School of Civil and Environmental Engineering
H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology, Atlanta, GA 30332, USA

Email: peeta@gatech.edu

ORCID: <https://orcid.org/0000-0002-4146-6793>

Irina Benedyk

Department of Civil, Structural and Environmental Engineering
University at Buffalo, Buffalo, NY 14260, USA

Email: birina@buffalo.edu

ORCID: <https://orcid.org/0000-0003-3971-0619>

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Abstract

Real-time travel information design with inadequate consideration of human factors can lead to driver distraction and diminish road safety. This study measures drivers' brain electrical activity patterns to evaluate multiple aspects of driver cognition and psychology under real-time information provision using insights from the neuroscience domain on the localization of brain functions. The brain electrical activity patterns of 84 participants are collected using an electroencephalogram (EEG) in an interactive driving simulator environment. The impacts of real-time auditory travel information characteristics (amount, sufficiency, and content) and different time stages of interaction with information provision (before, during, and after) on the frequency band powers of EEG signals in different brain regions are analyzed using linear mixed models. Study results illustrate that drivers exert more cognitive effort to perceive/process information on routes with complex driving environments. Insufficient information may evoke increased attention to internal processing and memory processing on routes characterized by higher travel time uncertainty, while route recommendation to switch to such routes may increase drivers' stress and anxiety. The study findings can aid information providers, both private and public, as well as auto manufacturers to incorporate driver cognition in designing safer real-time information and their delivery systems.

Keywords: Real-time information, Driver cognition, Driver psychology, Driving simulator, Electroencephalography (EEG), Linear mixed model

1. Introduction

The diversity of real-time travel information characteristics has increased over time due to advances in information and communication technologies. Advanced traveler information systems (ATIS) assist drivers in making more informed travel choices (for example, in terms of departure time and/or route choices) by providing them with pre-trip and en route real-time information (Ben-Elia and Avineri, 2015; Jou, 2001; Peeta and Yu, 2005; Yu and Peeta, 2011). Drivers now have access to multiple information sources (for example, public infrastructure and personal devices) that can provide a range of real-time travel information such as downstream traffic conditions, turn-by-turn navigation, weather and pavement conditions, and forward collision warnings through different delivery modes (for example, visual and auditory).

The provision of relevant and accurate en route information can provide several tangible and psychological benefits to travelers, including reduced travel time uncertainty and increased decisiveness (Ettema and Timmermans, 2006; Song et al., 2017). However, delivering ill-designed or untimely real-time information can lead to information-induced cognitive overload and/or detrimental psychological effects. This can have negative safety implications for both the system and the drivers, and adverse effects on drivers' experience with and trust in information systems (Abe and Richardson, 2006; Birrell and Young, 2011; Green, 2000). Even well-designed information can have severely reduced benefits for drivers depending on their cognitive and psychological states, such as insufficient attention or stress (Brookhuis and de Waard, 2010). The complexity and amount of information is bound to increase even further in the era of connected and automated transportation. Hence, it is critical to evaluate the cognitive and psychological effects of real-time travel information for improving the safety, effectiveness, and trustworthiness of ATIS. This study addresses this issue by analyzing the impacts of real-time travel information characteristics (amount, sufficiency, and content) on different aspects of driver cognition and psychology.

Several studies have evaluated the impacts of information provision on driver decision-making behavior and driving performance. Most existing driver behavior models under real-time information provision capture the impacts of road/route characteristics, generalized travel costs (for example, travel time and fuel consumption), heterogeneity in individual characteristics (for example, age and trip purpose), and real-time information characteristics (for example, amount and content) (Agrawal et al., 2016; Ben-Elia et al., 2013; Bonsall, 1992; Dia, 2002; Han et al., 2013; Peeta et al., 2000; Peeta and Yu, 2004, 2002). Some route choice models capture the role of information accuracy (Ben-Elia et al., 2013), multiple information sources (Hato et al., 1999), and past experience with information (Ben-Elia et al., 2008). Others analyze the compliance of drivers towards real-time travel information (Chen et al., 1999; Srinivasan and Mahmassani, 2000), and the heterogeneity in value of real-time travel information for drivers (Chorus et al., 2006; Kim and Vandebona, 1999; Zhang and Levinson, 2008). A few driver route choice models have been proposed based on well-defined behavioral theories, such as bounded rationality (Gao et al., 2011), prospect theory (Razo and Gao, 2013), and regret theory (Chorus et al., 2008), to capture the heterogeneity in decision-making. Paz and Peeta (2008, 2009a, 2009b, 2009c) developed traffic routing models under real-time travel information provision that are consistent with drivers' behavioral responses (for example, compliance) towards different information characteristics.

However, the aforementioned models often assume seamless perception, processing, and utilization of real-time information by drivers in an already cognition-heavy driving task. Thereby, they ignore information-induced cognitive load and task demand (for example, attention to internal processing, memory retrieval, and memory processing) that can increase driver distraction and/or reduce the utilization of real-time information in making routing decisions. This is important because such cognitive aspects can deteriorate driving performance and reduce road safety. In addition, these models do not explicitly consider the psychological effects (for example, stress and anxiety) of information content (for example, route recommendations or unfavorable travel information) that may impact drivers' route choice decision-making process.

Efforts to incorporate the impacts of real-time travel information that go beyond tangible benefits to drivers and seek to factor the psychological effects of information to model driver decision-making behavior are very sparse (Song et al., 2017). Even these models rely on subjective measures (for example, self-reported questionnaires) to estimate the psychological effects of information, which are collected post-experience and are often criticized for their associated memory biases such as source misattribution and transience as well as absent-mindedness and individual biases and beliefs (Choi and Pak, 2005; Schacter, 1999; Spector, 1994). This study uses physiological indicators around information provision (before, during and after) to analyze the cognitive and psychological effects of real-time travel information.

Some studies analyze driver interactions with in-vehicle infotainment systems (IVISs) using either the driving or secondary-task performance. For example, Maciej and Vollrath (2009) evaluate the roles of deviations in lateral position, eye gaze behavior, and subjective measures of distraction under manual- and speech-based IVIS interactions. Coleman et al. (2016) use the detection-response task to estimate cognitive workload under an interactive voice-based IVIS. Jamson and Merat (2005) report a reduction in driving performance (for example, reduced speed, and shorter time-to-collision) while interacting with visual or auditory IVISs. Pettitt et al. (2007) employ the GOMS (Goals, Operators, Methods and Selection Rules) approach to model the visual demand of an IVIS. Abe and Richardson (2006) analyze driving performance and subjective measures of trust-in-system to evaluate real-time collision warning systems. Related to information modality, past studies have associated auditory information with better driver performance in terms of reaction time compared to visual information (Liu, 2001; Ma et al., 2016). Although these studies use objective measures to estimate driver cognitive performance, driving and secondary-task performance measures fail to capture the cognitive and psychological impacts of information. This is because they mainly inform on the level of distraction or workload distribution due to the secondary task, while driving performance measures are unable to differentiate between the inattention blindness towards information and the ease of perception and processing. Moreover, the impacts of interactions with real-time travel information are likely to be different from those of non-travel related information systems. In this study, we evaluate the cognitive and psychological impacts of auditory real-time travel information on drivers by analyzing empirical physiological data, which provide direct insights on driver cognition and psychology compared to secondary-task or driving performance.

Advances in biosensing technologies and driver monitoring systems have provided capabilities for unobtrusive, real-time driver psychophysiological analysis. Past studies have developed methods to estimate driver's level of attention and mental workload associated with information

systems using physiological factors such as eye blink/gaze behavior (Benedetto et al., 2011; Faure et al., 2016), heart rate (Heine et al., 2017; Tjolleng et al., 2017), brain electrical activity (Berka et al., 2005), facial expressions, or a combination thereof (Haak et al., 2009; Ji et al., 2004). Previous studies have also linked physiological measures like eye fixation duration with visual information processing speed (Calsavara et al., 2021). Further, there is a growing consensus that brain electrical activity data collected using EEG provides better estimates of human attention compared to other physiological data such as functional magnetic resonance imaging (fMRI), functional near-infrared (fNIR) spectroscopy, galvanic skin response, heart rate variability, and pupillometry (Berka et al., 2007; Wilson, 2002). The localization of the physiological manifestations of different cognitive and psychological states in different regions of the brain allows for a more detailed analysis compared to other physiological indicators. However, most existing EEG studies in the driving context are limited to assessing driver fatigue (Gharagozlou et al., 2015; Jagannath and Balasubramanian, 2014; Jap et al., 2009; Kar et al., 2010; Li et al., 2012; Morales et al., 2017; Zhao et al., 2012), drowsiness or sleep deprivation (Barua et al., 2019; Brown et al., 2013; Chen et al., 2018; Johnson et al., 2011; Lin et al., 2005; Perrier et al., 2015), stress (Sciaraffa et al., 2022), and distraction (Almahasneh et al., 2014; Sonleitner et al., 2014). Very few efforts have been made to model driver behavioral aspects using EEG. For example, Yang et al. (2018) developed a classification algorithm for driving aggressiveness and stability based on EEG measures. Even these studies use oversimplified driving environments (in terms of traffic interactions and road characteristics) and, therefore, do not account for the differences in the cognitive effort required to drive in environments with different complexities while interacting with real-time information delivery systems. This study bridges this critical gap by implementing a network-level driving simulator environment with real-world dynamic traffic characteristics to analyze the cognitive and psychological effects of driving environment complexity and auditory real-time travel information by analyzing EEG data. Further, our experiment design elicits realistic attitudes and behaviors towards real-time information from the participants by enabling intent through novel compensation mechanisms (please see details in Section 2.3) and ensuring that route choices have perceptible impacts on their travel time.

To design safe and effective real-time information and their delivery systems, it is critical to understand the cognitive and psychological impacts of real-time information systems for the following reasons: (i) drivers' cognitive efforts (for example, internal processing, memory retrieval, and memory processing) to perceive and process information impact its utilization in making route choice decisions, (ii) changes in drivers' cognitive states (for example, distraction and inattention) can have considerable impacts on driving performance that may affect road/driver safety, and (iii) changes in psychological states (for example, anxiety and stress) can impact drivers' routing decisions and have direct implications for the evolution of traffic network flows. In this context, this study analyzes the latent cognitive and psychological effects of different real-time auditory travel information characteristics, including amount (i.e., the units of information in a message provided to the driver) (Dudek, 2004), sufficiency (sufficient vs. insufficient), and content (descriptive travel times vs. prescriptive route recommendation) in the different time stages of interaction with information provision (before, during, and after). In this study, sufficient information means that the drivers are provided information on the current and alternative routes, while insufficient information corresponds to no information on the alternative route. We also

investigate these latent effects on routes (freeway and arterial) with different driving environment complexities in terms of road characteristics, traffic interactions, and travel time uncertainty. Further, we analyze drivers' brain electrical activity patterns using EEG to investigate multiple aspects of information-induced cognitive and psychological effects that are associated with different regions of the brain. The study results and insights can aid information providers and auto manufacturers to incorporate driver cognition in designing real-time information systems to enhance road safety and improve user experience. They also enable the development of improved hybrid driver behavior models that factor the cognitive and psychological effects of real-time information provision.

In summary, this study contributes to the existing literature by addressing the following key gaps. First, existing studies analyze the impacts of external factors (for example, information, road, and individual characteristics) on drivers' behavioral responses, but do not analyze the latent cognitive processes that regulate these responses. This study investigates the impacts of information and route characteristics (driving environment) on driver cognition before, during and after information provision. This is critical because drivers' processing of information is neither seamless nor restricted to content alone, but also impacted by cognitive and psychological aspects. That is, their ability to comprehend the information in an inherently multi-tasking environment and their psychological states (for example, their stress level) at that time contribute to how much information they absorb and what they do with it. Second, this study analyzes EEG data to estimate driver cognition under real-time travel information provision by drawing insights from the neuroscience literature. Unlike indirect measures (for example, surveys and driving or secondary-task performance), EEG analysis can help create a detailed profile of drivers' cognitive and psychological states under information provision due to the localization of brain functions. Thereby, insights can be drawn directly based on empirical physiological data rather than through indirect measurements. Third, according to the Multiple Resource Theory (Wickens, 2008), humans have limited cognitive resources that are allocated across different tasks. By using simple driving environments to collect data, previous studies ignore the interactive cognitive impacts of driving environment complexity and real-time information characteristics. This study designs a driving simulator environment with a network-level setup featuring routes with different complexity and dynamic ambient traffic to analyze their impacts on driver cognition and psychology under auditory real-time travel information. Thereby, it enables a more realistic driving experience, which can be used to extract more realism in terms of the behaviors/attitudes of travelers to capture the linkages between information characteristics and driving environment complexity. Fourth, and synergistic with the previous contribution, novel mechanisms are used to elicit intent from the driving simulator participant related to the driving objective, as drivers would in the real world (for example, the need to be at the airport by a certain time to catch a flight).

The remainder of the paper is organized as follows. Section 2 discusses the driving simulator and accessory equipment used, experiment design, implementation procedure, data collection, and data analysis methods. Sections 3 and 4 presents and discusses the analysis results. Finally, Section 5 concludes the paper by summarizing the study findings and limitations and providing future research directions.

2. Methodology

2.1 Driving Simulator

This study uses a fixed-base driving simulator featuring a full-scale driving cockpit with automatic gear box, turn signals, and steering wheel with force feedback. A network-level setup that replicates the northern loop in Indianapolis, Indiana is created using OKTAL SCANeRStudio® 1.4 software (OKTAL, 2017). The driving environment is projected on three wide LCD screens that provide a field-of-view of around 120 degrees. As illustrated in Figure 1, the drivers (study participants) can choose between two routes, freeway (blue) and arterial (yellow), to reach their destination, and have two potential locations to switch routes during the trip. To ensure a realistic driving environment, a microscopic traffic simulator (AIMSUN 6.2) is integrated in real-time with the driving simulator to generate dynamic and responsive ambient traffic consistent with two traffic condition scenarios (with and without road accident). The two routes have different driving environment complexity in terms of the speed limit, number of intersections/interchanges, density of road objects (for example, street name sign or traffic signal), and traffic interactions. Further, the larger driving environment complexity of the arterial route results in larger travel time uncertainty compared to the freeway route. This enables analyzing the differences between the cognitive and psychological effects of different real-time travel information characteristics on routes with different complexity. A road network map displaying the drivable roads in grey and the participant vehicle's current GPS location in the simulator is provided on a tablet screen that is placed on the simulator dashboard as illustrated in Figure 2. Each route has two auditory personalized travel information (i.e., information customized to the destination) provision locations and two accident locations (as illustrated in Figure 1). Freeway route also has provisions for visual public travel information (i.e., information to specific landmarks on the road network) via variable message signs (VMSs), which are located beyond the locations at which auditory information is provided. The maximum number of accidents in each experiment run is set to one.

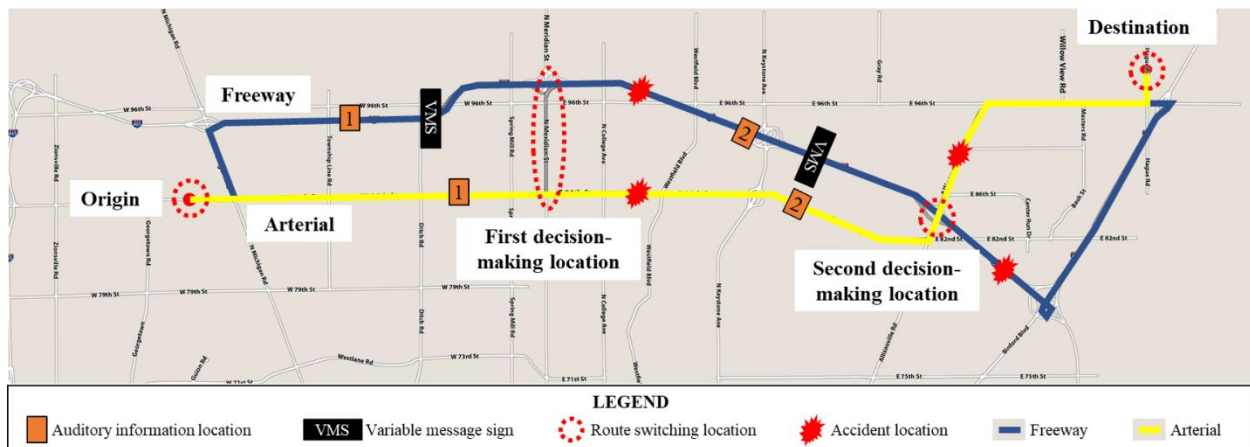


Figure 1 Experiment network setup illustrating real-time information provision locations

2.2 Scenario Design

Four auditory real-time travel information provision scenarios are created. They include: (i) no information (NI), (ii) travel time on current route (CT), (iii) travel times on current route and alternative route (AT), and (iv) prescriptive information informing drivers about downstream congestion and recommending alternative route (PI). CT provides insufficient travel information to the drivers; that is, no information is provided on the alternative route or route recommendation. PI is available only in scenarios with road accident. Eight scenario sets are designed to reduce the combinations of information scenarios and traffic condition scenarios. A single scenario set contains three runs with two distinct information scenarios at each information provision location. More details on the scenario sets can be found in Appendix I. The information is delivered through multimedia speakers positioned on each side of the driving cockpit below the screens. The auditory information is repeated (i.e., two instances of same information) immediately after the first instance to provide an additional opportunity to the participants in case they miss the first instance. Each scenario is characterized by different amount (i.e., the units of information in a message provided to the driver), sufficiency (sufficient vs. insufficient), and content (descriptive travel times vs. prescriptive route recommendation) of information to investigate the cognitive (for example, increased attention to internal processing, memory retrieval, and distraction) and psychological (for example, increased anxiety and stress levels) impacts of real-time travel information on drivers. The information scenarios are designed such that the alternative route is either more attractive due to longer travel time on the current route or is recommended by the information due to downstream congestion on the current route. This study uses data only near the first auditory information provision location (labeled as “1” in Figure 1) to avoid the interaction effects associated with multiple sources of information on freeways (i.e., personalized and public) and the multiple times real-time information is provided during a single trip.



Figure 2 Driving simulator

2.3 Participants

The study participants were recruited from the Greater Lafayette, IN community through advertisements in a university-wide email newsletter (at Purdue University), paper fliers, and word of mouth. The following criteria were used to recruit participants: (1) being 18 years of age or older, (2) having a valid driver's license, (3) not wearing corrective glasses (as we also collected

eye tracking data using wearable glasses), (4) having no predisposition to motion sickness, and (5) not self-reporting physical or mental impairments. The participants were chosen based on convenience sampling that met the aforementioned inclusion criteria. Potential participants signed up for an on-site simulator experiment session at the study experiment website by providing the requested information. Since certain medications and caffeine ingestion can affect EEG patterns (Blume, 2006; Pritchard et al., 1995) and, thereby, EEG data quality, participants were asked to not consume any medication or caffeine for at least 8 hours prior to the experiment. All recruited participants self-reported no medication or caffeine ingestion within the stated time period. Informed consent was obtained from all participants who visited the driving simulator laboratory.

Participants arriving for the driving simulator session were first familiarized with the simulator environment through a practice run on the network setup shown in Figure 1. Those showing motion sickness at this stage were not allowed to proceed further. Participants were informed that the freeway route is 16 miles long and it takes 21 minutes, on average, to reach destination under normal traffic conditions, while the arterial route is 11 miles long but takes about 25 minutes under normal conditions. The practice run started from the intersection before the first information provision location on the arterial route. During the run, participants were instructed to switch to the freeway route at the first decision-making location and then switch back to the arterial route at the second decision-making location. The run ended soon after the participant went past the second decision-making location. Through the practice run, a basic level of familiarity with the road network and information sources was created for all participants. Fast-forwarded driving videos of both routes were shown to each participant, with several pauses to illustrate important sign boards and turns to enhance familiarity with the study network. Next, participants were equipped with the EEG and completed an EEG baseline test in the B-Alert software (B-Alert, 2009) in a quiet room. After the test, they were equipped with wearable eye tracking glasses. This study does not use data from the EEG baseline test and the eye tracker. To verify EEG data acquisition, participants completed another simulated run following simple on-screen instructions (for example, “stay in the middle lane” and “maintain speed limit”). Then, each participant was asked to execute three simulator runs from the origin to the destination using randomly-assigned scenario sets. The order of scenarios within a scenario set was randomized. Participants were instructed to drive as if they were commuting to work, and compensated up to \$60 using a point-based reward system that tracked their intent to complete the trip within the assigned time limit (that is, the work start time) and their compliance with traffic rules and safe driving actions. They were aware of the maximum compensation for the study, and that reward and penalty points would be based on their intent to meet the work start time and their driving actions. However, they were not aware and, hence, could not track the actual points gained or lost with time at any point of the experiment runs. The experiment protocol was approved by the Purdue University’s Institutional Review Board (protocol # 1304013546).

125 participants were recruited in total for the experiment, out of which only 92 completed all three runs with valid EEG data (discussed in Section 2.4) around the first auditory information provision location. The data is further filtered down to 84 participants to include only right-handed participants as dexterity has been known to cause differences in brain activity (Bernard et al., 2011). The final participant pool consists of 45 males (27.2 ± 6.7 years) and 39 females ($25.0 \pm$

7.0 years) as illustrated in Figure 3. Figure 4 illustrates the distribution of information scenarios grouped by the route traveled at the first information provision location for all experiment runs.

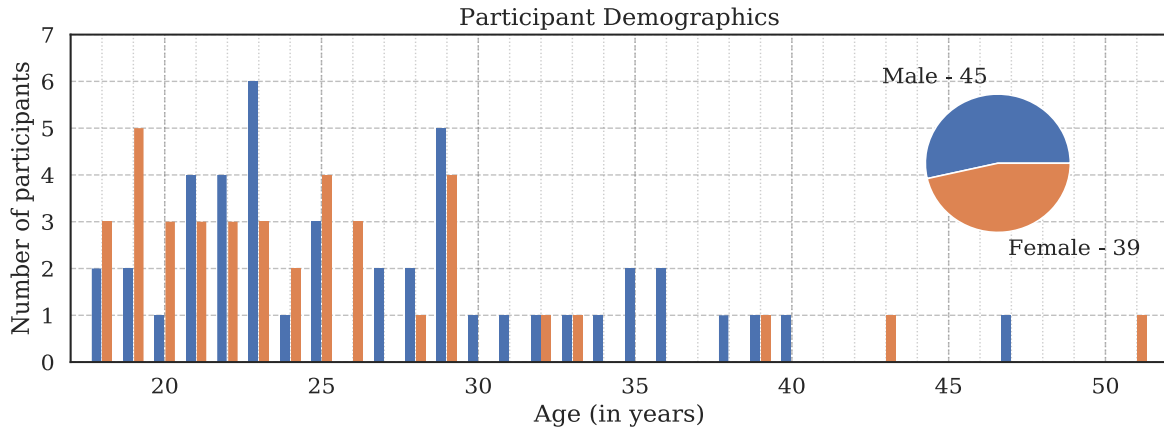


Figure 3 Participant age and gender distribution

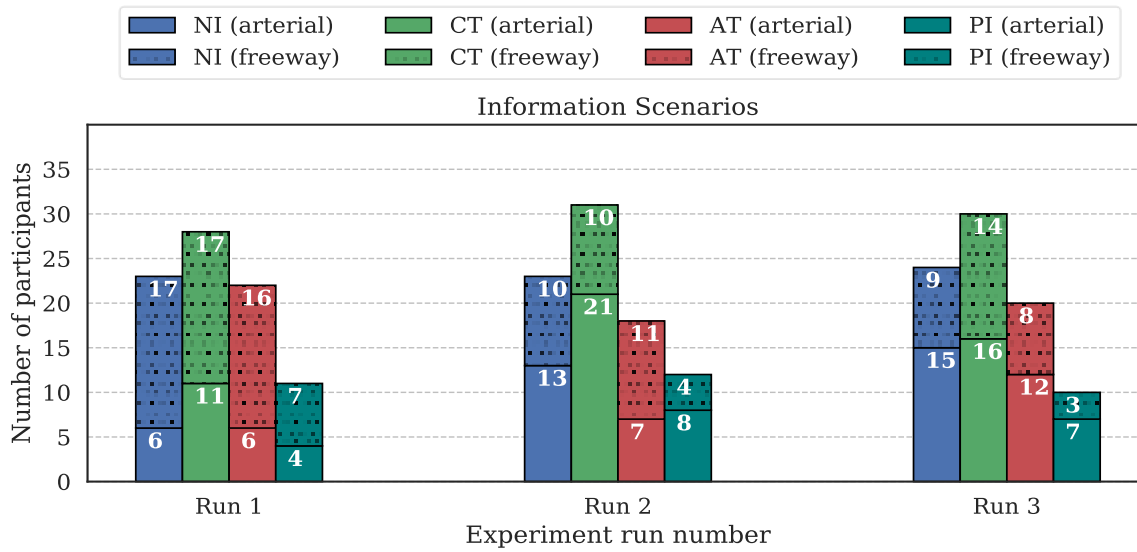


Figure 4 Information scenario distribution by route and experiment run

2.4 Electroencephalogram (EEG)

EEG measures the underlying electrical activity of the brain, mainly cerebrum, using electrodes (small metal disks) that are placed on the scalp. The cerebrum is the largest portion of the human brain and can be divided into four regions/lobes as illustrated in Figure 5: frontal, parietal (or centroparietal), temporal and occipital. The functionalities of each brain lobe have been extensively discussed in the neuroscience literature. The frontal lobe plays an important role in task planning, working memory, attention, and language articulation (Chayer and Freedman, 2001). It also shares the semantic and syntactic processing of auditory information with the temporal lobe (Friederici, 2011). The parietal lobe is associated with verbal-semantic processes

(Doppelmayr et al., 2005) and visual attention (Bisley and Goldberg, 2010). The parietal and frontal lobes are also responsible for body motor functions (Marcus and Jacobson, 2011). The temporal lobe is generally associated with auditory information perception, memory, and language interpretation, while the occipital lobe is associated with visual information processing (Abhang et al., 2016a).

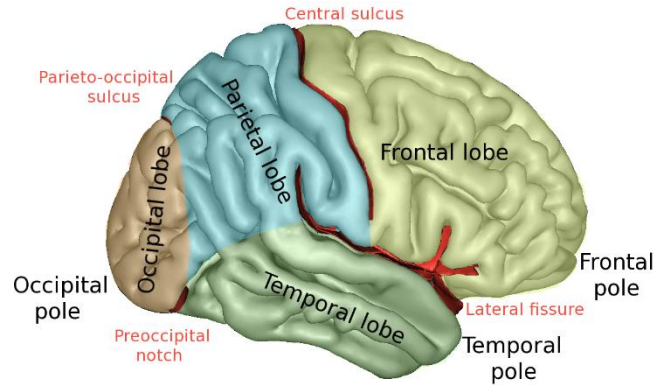


Figure 5 Human brain anatomy (Wikipedia, 2020)

Data on drivers' brain electrical activity is collected using a B-Alert X24 EEG system (Advanced Brain Monitoring, 2017). The EEG electrodes (also known as *EEG channels*) were placed according to the International 10-20 system as shown in Figure 6 (Klem et al., 1999). The brain regions and their corresponding EEG channels are shown in Table 1. The mastoids are used as a reference for measuring electrical signal; a mastoid is a bone located behind the ear. The data is collected using a sampling rate of 256 Hz.

Table 1 Brain regions and corresponding EEG channels

Brain Region	EEG Channels
Frontal lobe	Fp1, Fp2, F3, F4, Fz, F7, F8
Temporal lobe	T3, T4, T5, T6
Parietal lobe	P3, Pz, P4, C3, C4, Cz
Occipital lobe	O1, O2
Mastoids (EEG reference)	A1, A2

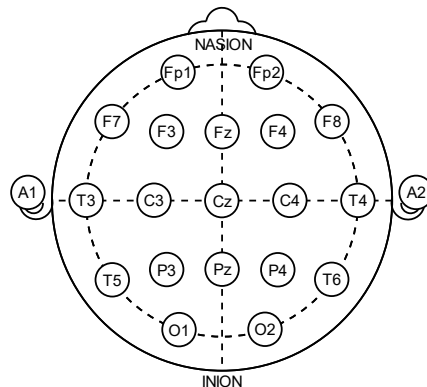


Figure 6 EEG electrode locations as per International 10-20 (Wikipedia, 2019)

Prior to data analysis, raw EEG signal is processed to remove contaminations (also known as *artifacts*). Advanced Brain Monitoring's B-alert software is used to remove five types of known artifacts: EMG (electromyogram for muscle movement), eye blinks, excursions, amplifier saturations and spikes (B-Alert, 2009). The EEG signal is then divided into epochs of 1-second duration, and power spectral density (PSD) (i.e., decomposition of signal power over a frequency range) of each epoch is computed by performing fast Fourier transformation. Next, the PSD for each epoch is averaged over 3 epochs by applying a 50% overlapping window to smoothen the data. This study analyzes the EEG signal power within four frequency bands (also known as *EEG bands*): delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz) and beta (13-30 Hz). The signal power of each band is calculated by averaging the PSD within its frequency bandwidth. Four time windows around the information provision location are defined to evaluate the information impacts at different time stages of interaction as illustrated in Figure 7: (i) 10 seconds before the information provision (t_0), (ii) first instance of the information (t_1), (iii) second instance of the information (t_2), and (iv) 10 seconds after the information (t_3). The information time length varies between 5 to 10 seconds depending on the scenario. The average log-power of every band (hereafter referred to as *band power*) for each time window is computed by averaging respective 1-second epoch band powers.

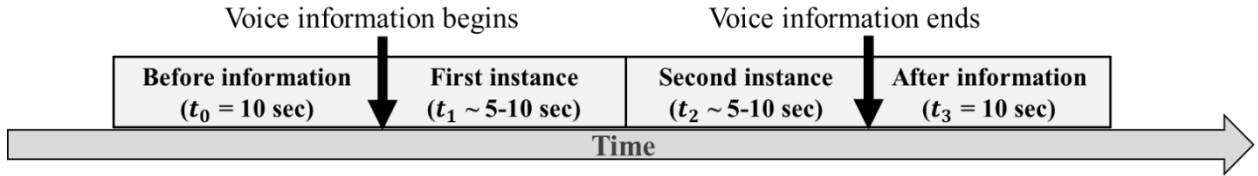


Figure 7 Time windows in the vicinity of the information provision location

In addition to being linked to the functionalities of each brain lobe, the EEG band powers are also associated with certain cognitive and psychological processes. The delta band power is most prominent when a person is in deep sleep (Abhang et al., 2016b). But in a wakeful state, such as when driving, the delta band power increases with increased attention to internal processing and/or memory retrieval (from long-term memory) by temporarily suppressing non-relevant neural activities related to external perception (Harmony, 2013; Harmony et al., 1996). Similar to the delta band, higher theta band power is generally associated with drowsiness and fatigue (Brown et al., 2013; Craig et al., 2012; Klimesch, 1999), but it also increases when subjected to tasks that involve inward focus (Abhang et al., 2016b) and memory processing (in short-term memory) (Aftanas and Golocheikine, 2001; Klimesch, 1999). Thus, we expect that processing real-time travel information and information from road signs, and contextualizing them in relation to the trip would evoke higher delta and theta band powers as they require higher *task demand* (i.e., increased attention to internal processing, memory retrieval and memory processing). A higher alpha band power is associated with passive attention or relaxed state of mind (Abhang et al., 2016b), while a lower alpha band power indicates increased alertness/vigilance and expectancy (Aftanas and Golocheikine, 2001), simple memory tasks (Harmony, 2013), and sensory-intake tasks that require processing external stimuli (for example, auditory information) (Ray and Cole, 1985). Foxe et al. (1998) found higher alpha activity in the parieto-occipital region under the anticipation of auditory

information, suggesting a temporary disengaging of the visual attentional system. The beta band power increases with psychological stress and anxiety (Abhang et al., 2016b). It is also found to be higher under cognitive states such as focused attention to external stimulus (Abhang et al., 2016b) and increased arousal (Morales et al., 2017). Almahasneh et al. (2014) reported that drivers who are distracted by semantic tasks (for example, travel information perception) exhibit lower beta band power.

2.5 Data Analysis

Linear mixed models (LMMs; also known as *multilevel models*) are used to analyze the differences in band powers for each EEG channel (19 channels), EEG band (4 bands), run (3 runs), and route (2 routes). Unlike simple linear models, LMMs can analyze data with non-independent or correlated errors due to the underlying hierarchical structure in the data as would arise from repeated measurements involving each participant. LMMs incorporate both fixed effects (parameter does not vary) and random effects (parameter is treated as a random variable). In this study, fixed effects include routes, runs, information scenarios, time windows, and their four-way interactions. Further, to reduce the levels of interaction effects (i.e., to three-way interactions), we define a combined variable route-run r using their cartesian product, $r \in R = \{(x, y) : x \in \{\text{Freeway, Arterial}\} \text{ and } y \in \{\text{Run 1, Run 2, Run 3}\}\}$. Band powers in multiple time windows for each participant are modeled as dependent variables with normally distributed errors. No information scenario (NI), pre-information time period (t_0), and Freeway-Run 1 are chosen as references for information scenarios, time windows, and route-run, respectively. For each EEG channel and EEG band, the following LMM is estimated by pooling data together from all participants, time windows, routes, and runs:

$$b_{rtn} = \beta_0 + \beta_r + \sum_i^I \beta_{r,i} \delta_{rin} + \beta_{r,t} + \sum_i^I \beta_{r,i,t} \delta_{rin} + \gamma_n + \varepsilon_{rtn}, \quad \forall r, t, n \quad (1)$$

In Eq. (1), b_{rtn} denotes the band power for the route-run r in time window t for participant n , β_0 is the intercept, β_r is the coefficient for route-run r , and $\beta_{r,i}$, $\beta_{r,t}$, and $\beta_{r,i,t}$ are interaction effects coefficients for the corresponding route-run r , information scenario $i \in I = \{\text{CT, AT, PI}\}$, and time window $t \in T = \{t_1, t_2, t_3\}$. γ_n is the random effects coefficient for participant-repeated measures arising from band powers in the four time windows across all runs and ε_{rtn} is the normally distributed error term. δ_{rin} is the indicator variable for the information scenario i presented to participant n in the corresponding route-run r . LMMs are estimated using the *statsmodels* module in the Python programming language (StatsModels, 2019), which finds the maximum likelihood estimates of the model coefficients using an expectation-maximization algorithm.

The experimental scenarios are designed to create similar ambient traffic conditions across runs within the analysis timeframe (i.e., the four time periods in the vicinity of the information provision location) for each route. Driver interactions with the immediate surrounding vehicles (for example, lane change) can contribute to unwanted noise in the EEG data and, thereby, the model. However, this study deliberately allows such interactions to simulate realistic driving conditions and enhance the ecological validity of the study results. Moreover, the choice of NI and t_0 as references allow analyzing the real-time information impacts on drivers while segregating

the effects of systematic route characteristics (for example, road curvature and sign boards) and macroscopic traffic conditions (i.e., traffic density and speed).

3. Results

Due to the large number of coefficients from 76 LMMs (19 EEG channels $\times$ 4 EEG bands), we use a heatmap-based visualization to illustrate the results (see Appendix II for details of the visualization). The LMM results for the delta, theta, alpha, and beta bands are illustrated in Figure 8-Figure 11, respectively. Each figure illustrates a collection of heatmap-based visualization of the model coefficients for all EEG channels (hereafter referred to as *brain-maps*) grouped by experiment run (row) and routes (column). The upper-left brain-maps (i.e., NI- t_0) for each run and route represent the main effect of route-run (β_r), except for the freeway and run 1 which represents the model intercept (β_0). The other brain-maps in the first row of each run (i.e., NI- t_1 , NI- t_2 and NI- t_3) and the first column of each route (i.e., CT- t_0 , AT- t_0 and PI- t_0) represent the second-level interaction effects of route-run with the time stages ($\beta_{r,t}$) and the information scenarios ($\beta_{r,i}$), respectively, while the other brain-maps represent their third-level interaction effects ($\beta_{r,i,t}$). The changes in band powers (i.e., the model coefficients) due to the main and interaction effects are depicted as heatmaps, with red indicating positive values (i.e., marginal increase in the band power due to the effect) and blue indicating negative values (i.e., marginal decrease in the band power due to the effect). The model coefficients with statistical significance level of 99% ($p < 0.01$) and 95% ($p < 0.05$) are represented by solid circles and hollow circles, respectively, in the figures. Statistically non-significant model coefficients are also included in the figures to compare the impacts of information characteristics and time stages of interaction with information on EEG band powers. Such results can illustrate whether the cognitive or psychological state remains unchanged for the given stimulus and/or during the time period of interest (e.g., see Alonso et al., 2015; Jap et al., 2009; Simon et al., 2011). The model intercepts are significantly larger than the main and interaction effects, as the intercepts (i.e., NI- t_0 for run 1 on the freeway route) represent the base EEG band powers (i.e., brain electrical activity under the experimental conditions in the absence of a stimulus), while other coefficients represent the changes in EEG band powers relative to their corresponding intercepts. Further, the coefficients corresponding to the time window t_0 are of little interest as they represent the band powers before the information provision location rather than the effects of information, which may be affected by unobserved factors (e.g., fatigue, learning effects) across runs related to driving. The unobserved heterogeneity between participants across different time windows and runs is captured by the random effects parameter γ_n . The values of γ_n for the estimated 76 LMMs range between 0.009 and 0.079, with a mean and standard deviation of 0.038 and 0.018, respectively.

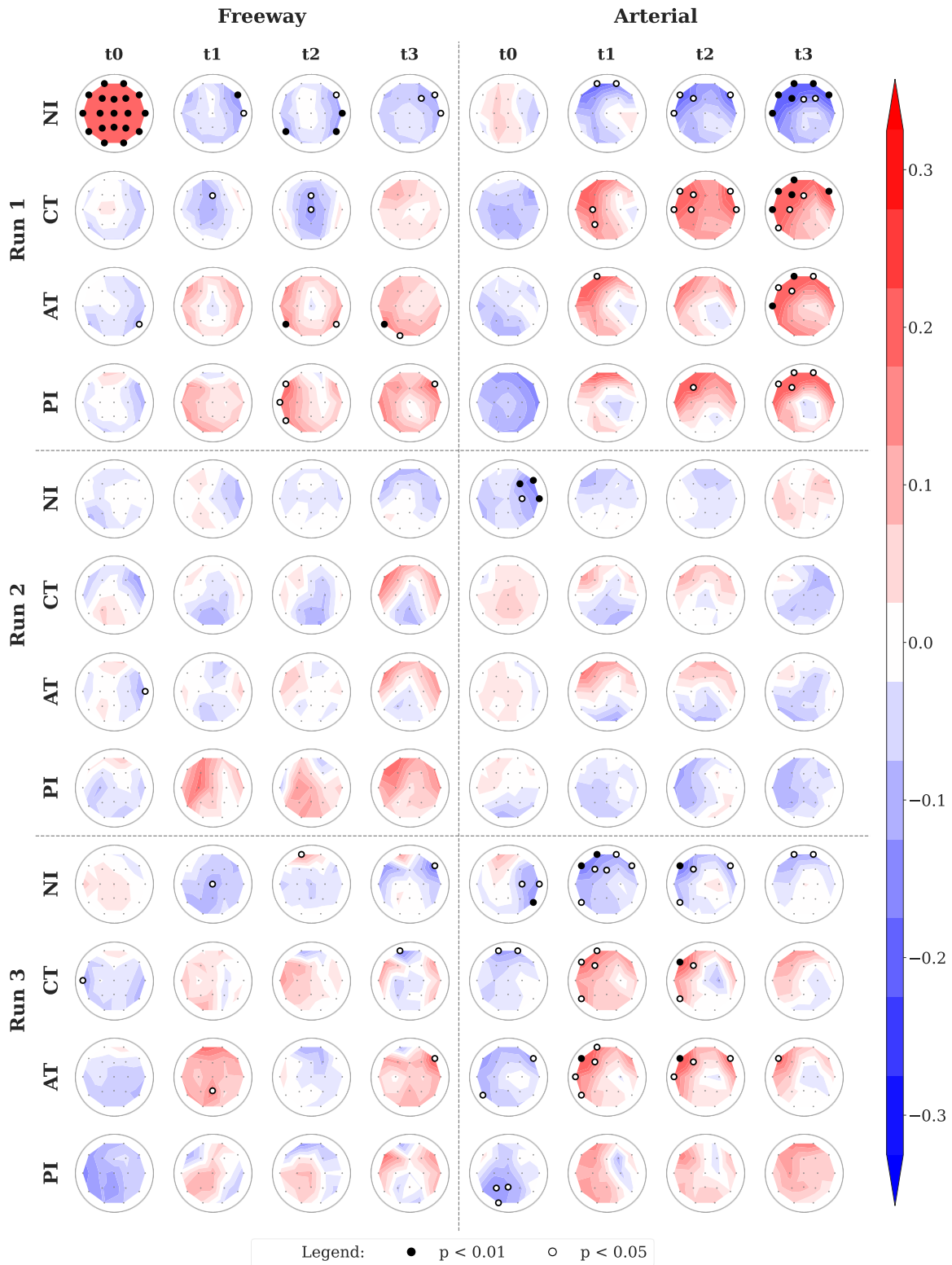


Figure 8 Linear mixed model results for the delta band

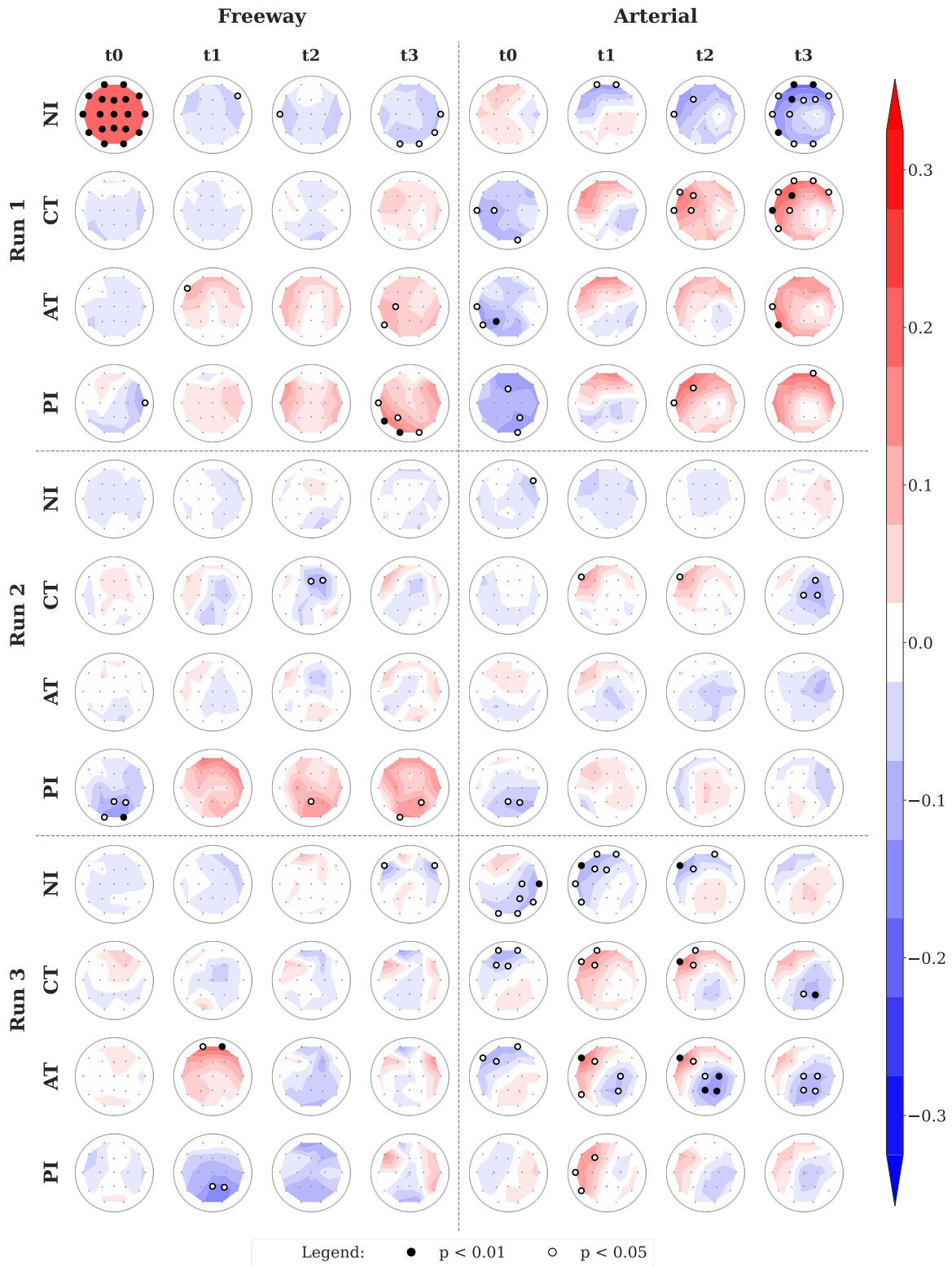


Figure 9 Linear mixed model results for the theta band

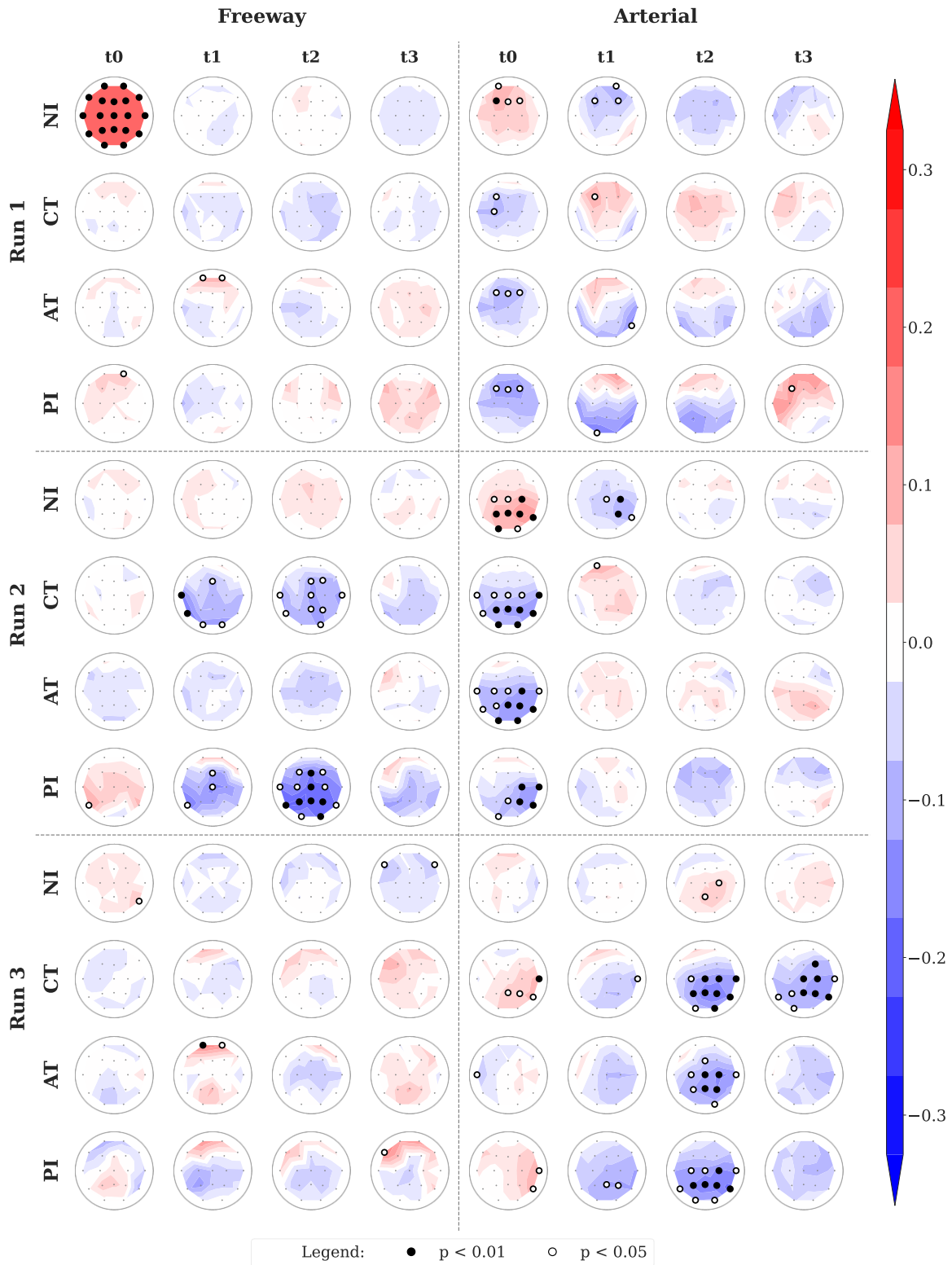


Figure 10 Linear mixed model results for the alpha band

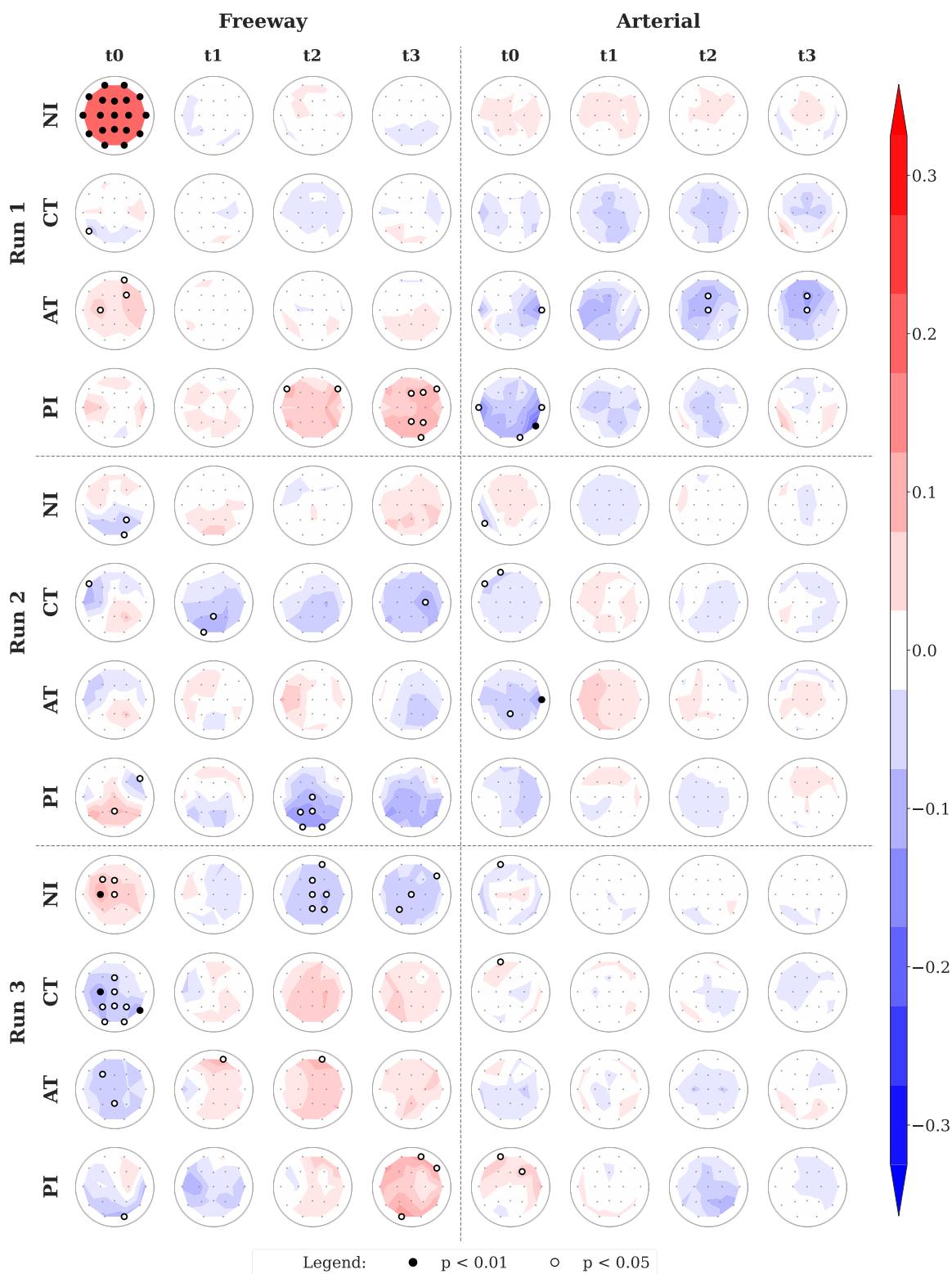


Figure 11 Linear mixed model results for the beta band

4. Discussion

This section discusses the cognitive and psychological effects of the driving environment complexity (i.e., route characteristics and macroscopic traffic conditions) and information characteristics, and their interactions, by analyzing the differences in band powers across runs, routes, information scenarios, and time windows in the vicinity of the information provision location. Other effects that arise from the experimental settings, including learning or familiarity effects and driver fatigue, are also discussed.

4.1 Effects of driving environment complexity

In the first experiment run (run 1), as participants do not have prior experience with information provision, the differences in band powers in Figures 8-11 under the NI scenario are likely caused by the systematic effects of the driving environment complexity. These differences are illustrated by the run 1 model coefficients of the NI scenario (i.e., NI- t_1 , NI- t_2 and NI- t_3 brain-maps) for both freeway and arterial routes. The results show little or no differences in the EEG band powers for the freeway route. The slightly lower delta and theta band powers as illustrated in Figures 8 and 9, especially in the sensory regions of the brain (i.e., temporal and occipital), indicate systematic impacts of the driving environment in the vicinity of the information provision location. This reasoning is further supported by the significantly lower delta and theta band powers for the arterial route, which has a more complex and dynamic driving environment than the freeway route. The steadily decreasing delta and theta band powers with time, mainly in the frontal and temporal regions of the brain, on the arterial route under NI are most likely caused by the diminishing task demand (i.e., attention to internal processing, memory retrieval, and memory processing) after drivers' interactions with the road objects providing trip-related information (for example, street name signs) upstream of the information provision location (i.e., during t_0). This is consistent with the study network as the first information provision location on the arterial route is immediately after an intersection comprising of several road objects (see Figure 1). These results indicate that the driving environment in the vicinity of the information provision location affects the EEG band powers.

The results also illustrate that the delta and theta band powers, mainly in the frontal and temporal regions of the brain, are higher and increase with time on the arterial route under information provision (CT, AT, and PI) in run 1, which indicates a higher task demand to process and contextualize the information. By contrast, the delta and theta band powers are either mostly unchanged (under CT) or higher (under AT and PI) on the freeway route in run 1. This suggests that drivers likely expended higher cognitive effort (in terms of the task demand) to process real-time travel information when driving in a more complex environment. Thus, providing real-time auditory travel information, such as from smartphones and radio, in complex driving environments could distract drivers from the primary driving task by diverting their cognitive resources towards internal processing, memory retrieval, and memory processing and, thereby, have negative implications for road safety. These findings are consistent with the existing body of literature that has reported higher levels of driver distraction while driving in complex road and traffic environments (see Young and Regan, 2007 for a review).

4.2 Effects of information characteristics

The results show that the differences in band powers because of the information characteristics (amount, sufficiency, and content) vary between the freeway and arterial routes. This indicates that the cognitive and psychological effects of real-time travel information differ between routes with different driving environment complexity. The differences in the cognitive effects arise because driving on routes with different complexity requires different amounts of cognitive resources for the driving task, and as per the Multiple Resource Theory (Wickens, 2008), affects the cognitive resources available for information perception and processing while driving. The psychological effects differ because they are associated with the ability and ease of making a routing decision (i.e., decisiveness). However, these routing decision characteristics depend on the information characteristics and the travel time uncertainties on the available routes (Ettema and Timmermans, 2006), which are based on their driving environment complexity. The interaction effects of the driving environment complexity and information characteristics on the EEG band powers are discussed in the next section.

4.3 Interaction effects of driving environment complexity and information characteristics

In run 1, the results illustrate that the delta (Figure 8) and theta (Figure 9) band powers increase with time under CT and are significantly higher compared to AT and PI on the arterial route, while these band powers are mostly unchanged under CT and are lower compared to AT and PI on the freeway route. These findings suggest that insufficient travel information (CT) induces higher task demand on drivers to process and contextualize the information when driving in a more complex driving environment. This could be because drivers typically seek more information when traveling on routes characterized by higher travel time uncertainty (i.e., the arterial route) (Ettema and Timmermans, 2006; Zhang and Levinson, 2008) and, therefore, expend more cognitive effort to retrieve and process information from their memory (i.e., task demand) when provided with insufficient travel information regarding their trip. This suggests that providing insufficient travel information in a more complex driving environment can significantly distract drivers from the driving task due to higher task demand. Thus, information providers (private or public) should either avoid providing insufficient information to drivers in complex driving environments or carefully weigh the advantages (for example, reduced travel uncertainty) and disadvantages (for example, reduced road safety) before providing such information.

In Figure 10, the slightly lower alpha band power in the temporal and occipital regions of the brain during the auditory information under AT and PI on the arterial route in run 1 compared to the mostly unchanged alpha band power under CT suggests that drivers exhibit higher alertness and sensory-intake to perceive and process more information units (AT and PI have twice the amount of information units as CT). Similarly, in Figure 11, the slightly lower beta band power under AT compared to CT on the arterial route in run 1 illustrates a higher level of driver distraction from the semantic task (i.e., perceiving and processing auditory information) due to more amount of information. However, these band powers are mostly unchanged on the freeway route, indicating that the aforementioned cognitive effects of the information amount are exhibited primarily when driving in a complex driving environment. These findings illustrate an interesting tradeoff between information sufficiency and information amount (as they are typically positively correlated), where providing more units of auditory travel information and providing insufficient

information in a complex driving environment increases driver distraction. Thus, information providers should avoid providing redundant information that will not add to the information sufficiency. Further, the underlying cause of distraction due to the higher information amount is primarily related to information perception, and it will likely vary with the modality of information (for example, auditory and visual). However, in case of insufficient information, distraction is related to memory retrieval and processing, which is independent of the information modality. Further research comparing different information modalities can aid in better understanding their roles.

The beta band power under PI is higher after the first instance of auditory information (i.e., during t_2 and t_3) on the freeway route in run 1. By contrast, it is mostly unchanged on the arterial route. Sciaraffa et al. (2022) reported a high correlation between beta band power in the parietal region and level of stress during realistic driving in a simulator by benchmarking it against NASA-TLX, which they also validated in a controlled non-driving multitasking experiment. Thus, the observed increase in the beta band power (see Figure 11) suggests an increase in psychological stress and anxiety among drivers due to the recommended route switch to the arterial route, which is characterized by a higher travel time uncertainty. Therefore, while drivers expend lesser cognitive efforts to perceive and process the information on the freeway route, the recommendation to switch to the alternative route with higher travel time uncertainty due to downstream congestion on the current route results in a seemingly difficult route choice decision and induces stress and anxiety. The increased psychological stress and anxiety can adversely impact the consistency of drivers' route choice decision-making process. Consequently, it will reduce the reliability of traffic network flow predictions under real-time information provision in complex driving environments if it is not explicitly factored in route choice behavior models by traffic operators. It can also affect other aspects of driver behavior, such as car-following behavior (Paschalidis et al., 2019), which may impact road safety. Further, inadequate consideration of these psychological effects can negatively affect user experience with the information systems and reduce their trust in these systems.

4.4 Other effects

The differences in band powers in the second experiment run (run 2) are quite different than those in the first experiment run, which can be mostly attributed to the learning effects due to participants' increasing familiarity with the driving simulator, study network, and information sources. The third experiment run (run 3) is characterized by the combined impacts of learning, driver fatigue (participants have already spent around 2 to 2.5 hours in the laboratory by then), drowsiness, and the "end-spurt" effect that occurs when participants know that the experiment is in its final stage (Morales et al., 2017).

On the arterial route in run 2, the mostly unchanged delta and theta band powers under NI suggest reduced systematic effects of the driving environment, likely because of the reduced attention towards the road objects providing trip-related information before the information provision location. This is also supported by the slightly lower alpha band power in the parietal and temporal regions of the brain during t_1 , which could manifest from the expectancy of real-time information and simple memory task to pinpoint the information provision location from recognizable landmarks (i.e., road signs and built environment in the simulator) on the arterial

1 route. On the arterial route in run 3, the delta and theta band powers under NI are lower (similar to
2 run 1), but with reduced magnitude and an increasing trend over time. This could be because of
3 the quicker recognition of road characteristics due to increased familiarity with the study network.
4 These findings illustrate the learning (familiarity) effects of drivers with the driving environment
5 and real-time information systems. Previous studies have shown that increased familiarity with the
6 road environment can lead to automaticity or inattention blindness (Charlton and Starkey, 2013,
7 2011), which manifests as reduced mental demand to process the road environment. It also
8 illustrates the importance of providing real-time travel information consistently (by information
9 providers) at locations where drivers expect to receive information, to avoid unwanted
10 psychological stress and anxiety.

11 Some interaction effects of the driving environment complexity and information characteristics
12 can be observed from the results of runs 2 and 3. On the freeway route in run 2, the higher theta
13 band power under PI compared to CT and AT indicates a higher task demand when the descriptive
14 information is not provided. The significantly lower alpha band power under CT and PI suggests
15 an increase in simple memory tasks to recall missing travel time information for the alternative
16 route. The significantly lower beta band power under CT and PI suggests lower psychological
17 stress and anxiety upon receiving the information about the current route, likely due to drivers'
18 premeditated routing decisions (based on their prior experiences during the experiment) to not
19 switch to a route with higher travel time uncertainty (3 out of 4 drivers stayed on the freeway route
20 under PI in run 2 compared to 0 out of 7 drivers in run 1). There are little or no differences in the
21 EEG band powers under information provision (CT, AT, and PI) for the arterial route in run 2,
22 except for a slight increase in theta band power under CT that suggests an increase in inward focus
23 and memory processing under insufficient information.

24 On the arterial route in run 3, the delta and theta band powers in the left frontotemporal region
25 are higher under the descriptive information scenarios (CT and AT) similar to run 1 but decrease
26 with time unlike in run 1. This suggests a quicker memory retrieval and processing of the
27 information, which could be attributed to increased accessibility to relevant information in the
28 memory from repeated driving tasks in a short period of time. The lower theta power in the parietal
29 region under AT and CT could be a result of reduced drowsiness (Brown et al., 2013) upon
30 receiving descriptive auditory information. This illustrates the importance of developing integrated
31 real-time information and driver monitoring systems that information providers and automobile
32 manufacturers can use to mitigate driver drowsiness by providing descriptive information when
33 the system identifies a drowsy driver. The widespread decrease in the alpha band power under
34 information provision indicates higher alertness, simple memory tasks, and sensory-intake to
35 perceive and process external stimuli due to increasing familiarity with the driving simulator and
36 the driving environment. The EEG band powers under information provision (CT, AT, and PI) are
37 mostly unchanged on the freeway route in run 3.

38 A summary of the cognitive and psychological main and interaction effects of the driving
39 environment complexity and information characteristics, and their implications for different
40 stakeholders, is presented in Table 2.

41 As discussed before, the second and third experiment runs are affected by the overlapping
42 presence of learning effects with the equipment (i.e., driving simulator), study network, and
43 information sources as well as driver fatigue and drowsiness, which limits the ability of the current

- 1 experiment design to make concrete inferences on the cognitive and psychological effects of real-
- 2 time information for these runs. More focused experiment designs are needed to analyze the
- 3 impacts of learning, fatigue, and drowsiness on the cognitive and psychological effects of real-
- 4 time information provision.

Table 2 Summary of the cognitive and psychological effects of driving environment complexity and information characteristics

Run	Route	Scenario	Information characteristics	Observations		Inferences		Real-world implications
				EEG band	Physiological differences	Cognitive effects	Psychological effects	
Effects of driving environment complexity								
Run 1	Freeway	NI	-	Delta and theta	Slightly lower	Diminishing task demand after drivers' interactions with the road objects in a complex environment	-	-
	Arterial				Significantly lower and decreasing with time			
Run 1	Freeway	CT/AT/PI	Information provision	Delta and theta	Mostly unchanged or higher	Higher task demand to process information in a complex environment	-	Driver distraction due to information provision
	Arterial				Higher and increasing with time			
Interaction effects of driving environment complexity and information characteristics								
Run 1	Freeway	CT	Information sufficiency	Delta and theta	Mostly unchanged	Higher task demand to process and contextualize insufficient information in a complex environment	-	Driver distraction due to higher task demand
		AT/PI			Higher			
	Arterial	CT			Significantly higher and increasing with time			
		AT/PI			Higher			
Run 1	Arterial	CT	Information amount	Alpha	Mostly unchanged (in temporal and occipital regions)	Higher alertness and sensory-intake to perceive and process more information units in a complex environment	-	Driver distraction due to information perception
		AT/PI			Slightly lower (in temporal and occipital regions)			

Run 1	Arterial	CT	Information amount	Beta	Mostly unchanged	Higher level of driver distraction from a semantic task of perceiving and processing more information units in a complex environment	-	Driver distraction due to information perception
		AT			Slightly lower			
Run 1	Freeway	PI	Information content	Beta	Higher and increasing with time	-	Higher psychological stress and anxiety due to the recommended switch to a more complex route with higher travel time uncertainty	Adverse implications for modeling route choice behavior
	Arterial				Mostly unchanged			
Other effects								
Run 2	Arterial	NI	-	Delta and theta	Mostly unchanged	Reduced attention towards the road objects in a complex environment	-	-
Run 2	Arterial	NI	-	Alpha	Slightly lower	Expectancy of information and simple memory tasks to pinpoint information location in a complex environment	-	-
Run 2	Freeway	PI	Information content	Theta	Higher	Higher task demand in the absence of descriptive information	-	-
		CT/AT			Lower or mostly unchanged			
Run 2	Freeway	CT/PI	Information sufficiency and content	Alpha	Significantly lower	Increase in simple memory tasks to recall missing travel time information on the alternative route	-	-
		AT			Mostly unchanged			
Run 2	Freeway	CT/PI	Information sufficiency and content	Beta	Lower	-	Lower psychological stress and anxiety due to receiving information about the current route	Reduced stress and anxiety to reaffirm premeditated decisions
		AT			Mostly unchanged			

Run 3	Arterial	NI	-	Delta and theta	Lower and increasing with time	Quicker recognition of road characteristics due to increased familiarity compared to run 1	-	-
Run 3	Arterial	CT/AT	-	Delta and theta	Higher and decreasing with time	Quicker memory retrieval and processing of the information compared to run 1	-	-
Run 3	Arterial	CT/AT	Information content	Theta	Lower (in parietal region)	Reduced drowsiness due to receiving descriptive information	-	Descriptive information provision can help reduce driver drowsiness
		PI			Mostly unchanged (in parietal region)			
Run 3	Arterial	CT/AT/PI	Information provision	Alpha	Significantly lower	Higher alertness, simple memory tasks, and sensory-intake to perceive and process information due to increasing familiarity	-	-

5. Concluding Comments

An understanding of traveler interactions with information provided in an increasingly information-rich vehicular environment is critical to the design of user-friendly in-vehicle environments as well as information design and delivery. Poorly designed real-time information can have several negative implications for the driver as well as the transportation system. For example, increased driver distraction from real-time information can substantially increase the risk of road accident (Donmez et al., 2007). At the same time, the characteristics of real-time information and the cognitive effects induced from it have significant impacts on drivers' route choice decisions (Agrawal and Peeta, 2021), which consequently affects traffic patterns and can exacerbate level of congestion. In this context, this study evaluates the cognitive and psychological effects of real-time auditory travel information on drivers. EEG is used to measure drivers' brain electrical signals to estimate the information-induced cognitive and psychological effects in a network-level driving simulator environment in which drivers choose between two routes (arterial and freeway) with different driving environment complexity (in terms of route characteristics and macroscopic traffic conditions) to reach the destination.

Several mechanisms are designed to simulate realistic driving conditions and enhance the ecological validity of the study results. First, participants were provided with a driving objective (i.e., commute to work) to elicit driving intent. Second, a point-based reward system was employed to track their intent to reach the destination on time as well as their compliance with traffic rules and safe driving actions. Third, a microscopic traffic simulator was integrated with the driving simulator to generate responsive ambient traffic that enables participants to freely interact with the surrounding vehicles.

Four information scenarios with varying information characteristics (amount, sufficiency, and content) are created to provide drivers with real-time auditory travel information prior to making route choice decisions. The impacts of information characteristics and time stages of interaction with information (before, during, and after) on EEG band powers are evaluated using linear mixed models. The differences in band powers are analyzed to investigate the cognitive and psychological effects of the driving environment complexity, information characteristics, and their interactions. Three key inferences are obtained on the cognitive and psychological effects of real-time travel information provision on drivers. First, processing real-time auditory travel information while driving on a route with a complex driving environment (i.e., several road objects, complex traffic interactions, and higher travel time uncertainty) requires more cognitive effort and induces higher task demand (i.e., increased attention to internal processing, memory retrieval, and memory processing). Second, processing and contextualizing insufficient real-time travel information results in higher task demand when traveling on routes characterized by higher travel time uncertainty. However, perceiving and processing more amount of information requires more cognitive efforts from the drivers in a complex driving environment. Third, the recommendation to switch to a more complex route with higher travel time uncertainty (i.e., from the freeway route to the arterial route in this study) can cause higher psychological stress and anxiety among drivers, which may impact their route choice decision-making process.

The study provides a comprehensive analysis of several factors (i.e., information characteristics, time stages of interaction with information, and driving environment) that impact the cognitive and psychological effects of real-time travel information using drivers' EEG data. Information providers (private and public) and auto manufacturers can incorporate the insights from this study on the cognitive effects of information to design real-time information and its delivery systems for improving road safety and user experience. The study also contributes to improving the understanding of the psychological aspects of real-time information and their impacts on drivers' route choices, which can help traffic operators to better predict traffic network flows under real-time information provision.

Two limitations can be identified for this study. First, the sample population is skewed towards young adults (mostly under 30 years), which can affect the generalizability of the study results. This is partly due to instrumentation constraints (for example, no corrective glasses and predisposition to motion sickness). Second, the effects of learning, fatigue, and drowsiness are not controlled in the current experiment design. In future studies, such effects can be captured through focused experiment design and a sample that is correspondingly representative. Other future research directions include developing hybrid driver behavior models incorporating driver cognition and psychology estimated using physiological data under real-time information provision, evaluating other characteristics of real-time travel information (for example, source and modality), analyzing the impacts of pre-information cognitive states (for example, driver fatigue) on real-time information perception/processing and route choice decision-making behavior, comparing the cognitive and psychological effects of real-time information estimated using physiological data and self-reported survey data, and developing an integrated real-time information system and driver monitoring system to optimally design the information to be provided based on the driver's psychophysiological states.

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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. **Irina Benedyk:** Investigation, Methodology, Writing – Review & Editing.

Declaration of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix I

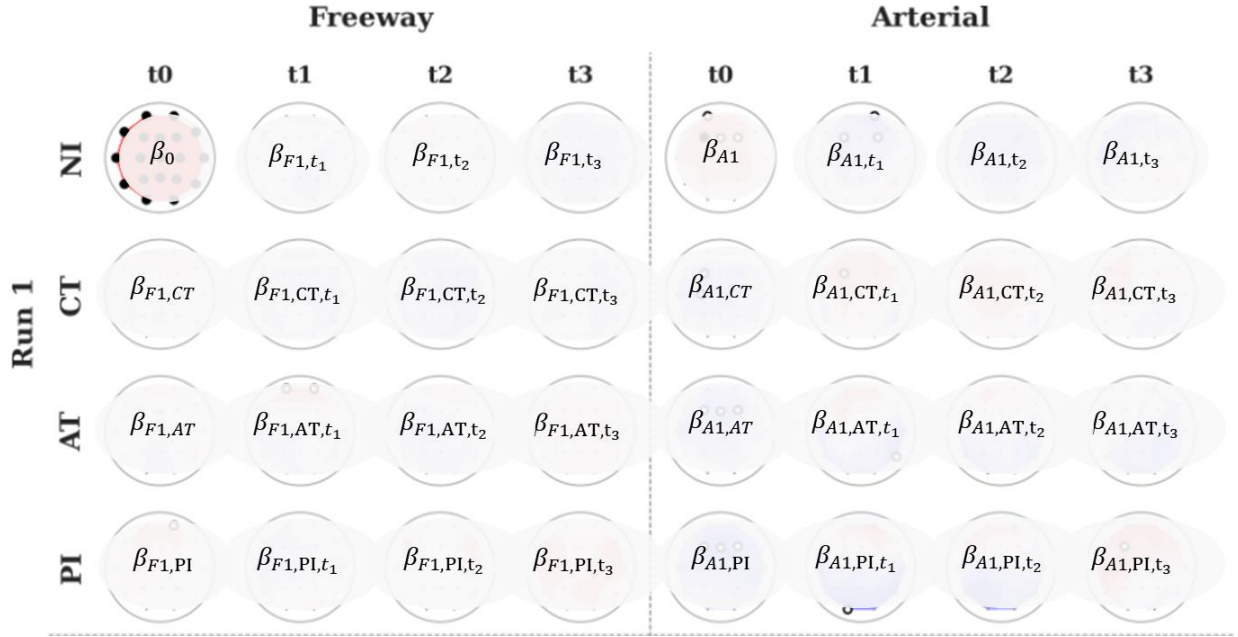
The table below illustrates the eight scenario sets used in this study with corresponding information scenarios and traffic condition scenarios. The order of scenarios within a scenario set is randomized.

Set Number	First Information Provision Location		Second Information Provision Location	
	Road Accident	Information Scenario	Road Accident	Information Scenario
1	No	AT	Yes	AT
	Yes	AT	No	AT
	Yes	PI	No	NI
2	No	NI	Yes	PI
	No	CT	Yes	CT
	Yes	CT	No	CT
3	Yes	CT	No	CT
	Yes	CT	No	CT
	Yes	AT	No	AT
4	No	CT	Yes	AT
	No	AT	Yes	AT
	No	AT	Yes	AT
5	No	NI	No	NI
	No	AT	No	AT
	Yes	AT	No	AT
6	No	NI	No	NI
	No	CT	No	CT

	No	CT	Yes	CT
7	Yes	NI	No	NI
	Yes	PI	No	NI
	Yes	PI	No	AT
8	No	NI	Yes	NI
	No	NI	Yes	PI
	No	CT	Yes	PI

1 Appendix II

2 The figure below shows the location of model coefficients (see Eq. (1)) of 19 LMMs (one for
3 each EEG channel) for the delta band in run 1 in a heatmap-based visualization. Model coefficients
4 that are found to be statistically significant at 99% and 95% levels of significance are illustrated
5 as solid circles and hollow circles, respectively, in the figure.



6
7 Note that “F1” and “A1” are abbreviations for Freeway-Run 1 and Arterial-Run 1, respectively.
8 Coefficients for other route-runs (i.e., F2, F3, A2, and A3) are positioned similar to that of Arterial-
9 Run 1 for their corresponding route-runs.