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Development of In-Vehicle Information Dissemination Mechanisms to Reduce Cognitive Burden in the Information-Rich Driving Environment

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Development of In-vehicle Information Dissemination Mechanisms to Reduce Cognitive Burden in the Information-rich Driving Environment

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16. Abstract
The diversity and complexity of real-time travel information provided en route to drivers has steadily increased over the years. While it generally has positive impacts by enabling drivers to make more informed travel choices with confidence, several studies have reported the possible negative implications of poorly-designed information delivery systems. The key reason for this underlying ineffectiveness is the lack of adequate consideration of human and psychological factors in real-time information design and its delivery. This study measures drivers' brain electrical activity patterns to evaluate driver cognition under real-time information provision using insights on the localization of brain functions from the neuroscience domain. 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 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 and process real-time information on complex routes in terms of the road environment and traffic interactions. Further, insufficient real-time travel information may evoke increased attention to internal processing and memory retrieval on routes characterized by higher travel time uncertainty. Also, driver anxiety may increase due to information recommending switch to routes with higher travel time uncertainty and complex driving environment. The study findings can aid information providers, both private and public, as well as auto manufacturers to incorporate driver cognition and psychology in designing real-time information and their delivery systems.

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1. INTRODUCTION

The diversity of real-time travel information has increased over the years with advances in information and communication technologies. Advanced traveler information systems (ATIS) assist drivers in making more informed travel choices (e.g., departure time choice and route choice) 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 (e.g., public infrastructure and personal devices) that can provide a variety of real-time information such as downstream traffic conditions, turn-by-turn navigation, weather and pavement conditions, and forward collision warnings in different modalities (e.g., visual and auditory).

The provision of relevant and accurate *en route* information can provide several benefits to travelers, including increased cognitive decisiveness and reduced travel time uncertainty (Ettema and Timmermans, 2006; Song et al., 2017). But concurrently, delivering ill-designed or untimely information can lead to information overload. This can have negative safety implications, 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 delivered to drivers can have severely reduced benefits depending on their cognitive state, 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. Thus, it is critical to evaluate the cognitive effects of real-time travel information for improving the effectiveness and trustworthiness of ATIS. This study addresses this issue by analyzing the impacts of real-time travel information characteristics (amount and content) on 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 (e.g., travel time and fuel consumption), heterogeneity in individual characteristics (e.g., age and trip purpose), and real-time information characteristics (e.g., 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). Some route choice models captured 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). A few studies have also analyzed 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). Although these theoretical models capture the limitations of human cognition and inconsistencies in human behavior, but they do not explicitly analyze the cognitive effects induced by real-time information. 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, these models often assume seamless perception, processing, and utilization of real-time information by drivers, and thereby,

ignore the human factors and psychological aspects on drivers' decision-making process in an already cognition-heavy driving task.

Limited efforts have been made to incorporate the impacts of real-time travel information that goes beyond the tangible benefits to the drivers by factoring the cognitive effects of information in modeling driver decision-making behavior (Song et al., 2017). But these models rely on subjective measures (e.g., self-reported questionnaires) to estimate psychological effects of information, which 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).

Previous studies have analyzed driver interactions with in-vehicle infotainment systems (IVIS) on drivers using either driving or secondary-task performance. For example, Maciej and Vollrath (2009) evaluated the deviations in lateral position, eye gaze behavior and subjective measures of distraction under manual- and speech-based IVIS interactions. Coleman et al. (2016) used detection-response task to estimate cognitive workload under interactive voice-based IVIS. Jamson and Merat (2005) reported reduction in driving performance (e.g., reduced speed and shorter time-to-collision) while interacting with visual or auditory IVIS. Pettitt et al. (2007) employed GOMS (Goals, Operators, Methods and Selection Rules) approach to model visual demand of IVIS. Abe and Richardson (2006) analyzed driving performance and subjective measures of trust-in-system to evaluate real-time collision warning systems. In the context of 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, secondary-task performance measures fail to capture the cognitive and psychological impacts of information as 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 inattention blindness towards information from ease of perception and processing. Moreover, it can be expected that the impacts of interactions with real-time travel information will be different from non-travel related information systems. In this context, we evaluate the cognitive and psychological impacts of auditory real-time travel information on drivers by analyzing their objective physiological data, that is, variations in driver's brain electrical activity measured using an electroencephalogram (EEG), which provide more direct insights on driver cognition compared to secondary-task or driving performance.

The advances in biosensing technologies and driver monitoring systems have enabled unobtrusive, real-time driver psychophysiological analysis. Some studies have developed methods to estimate driver's level of attention and cognitive 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 of them (Haak et al., 2009; Ji et al., 2004). 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 like functional magnetic resonance imaging (fMRI), functional near-infrared (fNIR) spectroscopy, galvanic skin response, heart rate variability, and pupillometry (Berka et al., 2007; Wilson, 2002). However, most 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), and distraction (Almahasneh et al., 2014; Sonnleitner et al., 2014), and that too in an oversimplified driving environment. A few efforts have been made in the past to model driver behavior using EEG. For example, Yang et al. (2018) developed a classification algorithm for driving aggressiveness and stability based on EEG measures. Therefore, to address the existing gap of cognitive assessment of information systems in a realistic driving environment, this study evaluates the cognitive and psychological impacts of auditory real-time information in a network-level driving simulation environment with dynamic ambient traffic by analyzing EEG data. The experiment design elicits realistic attitude and behavior towards real-time information from the participants as their route choices have considerable impacts on their travel time and compensation for participating in our experiments (more details are provided in Section 2.1). The real-world replica of a network-level roadmap also allows to capture the cognitive effects of road environment complexity on driver cognition.

This study draws inferences using insights from neuroscience literature for explaining the observed differences in drivers' brain electrical activities under auditory real-time travel information. A brief overview of EEG and brain functionalities is presented below.

EEG measures the underlying electrical activity of the brain, mainly cerebrum, using electrodes (small metal disks) that are placed on the scalp. Cerebrum is the largest portion of the human brain and can be divided into four regions/lobes (as illustrated in Figure 1): frontal, parietal, temporal and occipital. The functionalities of each brain lobe have been extensively discussed in the literature. 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). Parietal lobe is associated with verbal-semantic processes (Doppelmayr et al., 2005) and visual attention (Bisley and Goldberg, 2010). Parietal and frontal lobes are also responsible for body motor functions (Marcus and Jacobson, 2011). 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).

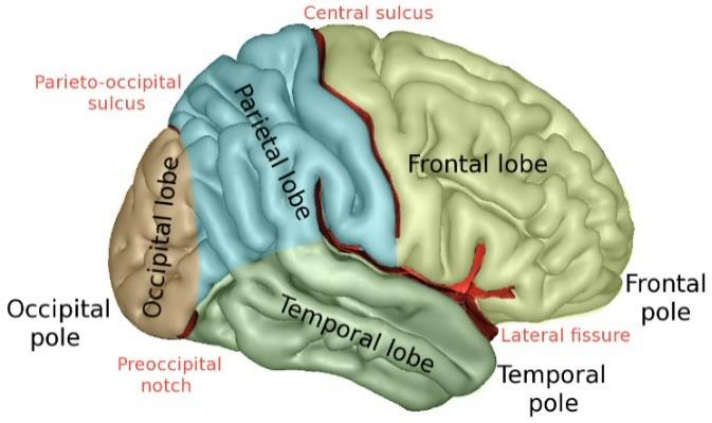

Figure 1 Human brain anatomy

2. METHODOLOGY

2.1. Driving Simulator

This study uses a fixed-base driving simulator equipment featuring a full-scale driving cockpit with automatic gear box, turn signals and steering wheel with force-feedback. A network-level roadmap that replicates real-world northern 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. The drivers can choose between two routes, freeway (blue) and arterial (yellow), to reach their destination and have two options to switch routes during the trip as illustrated in **Figure** 2. To ensure realistic driving environment, a microscopic traffic simulator (AIMSUN 6.2) is integrated to generate dynamic and responsive ambient traffic consistent with the two traffic condition scenarios (with and without road accident). A road network map displaying drivable roads in grey highlight and vehicle's current GPS location in the simulator is provided on a tablet screen which was placed on the simulator dashboard as illustrated in **Figure** 3. Each route has two information provision locations and two accident locations (as illustrated in **Figure** 2). The maximum number of accidents in each experiment run is limited to one.

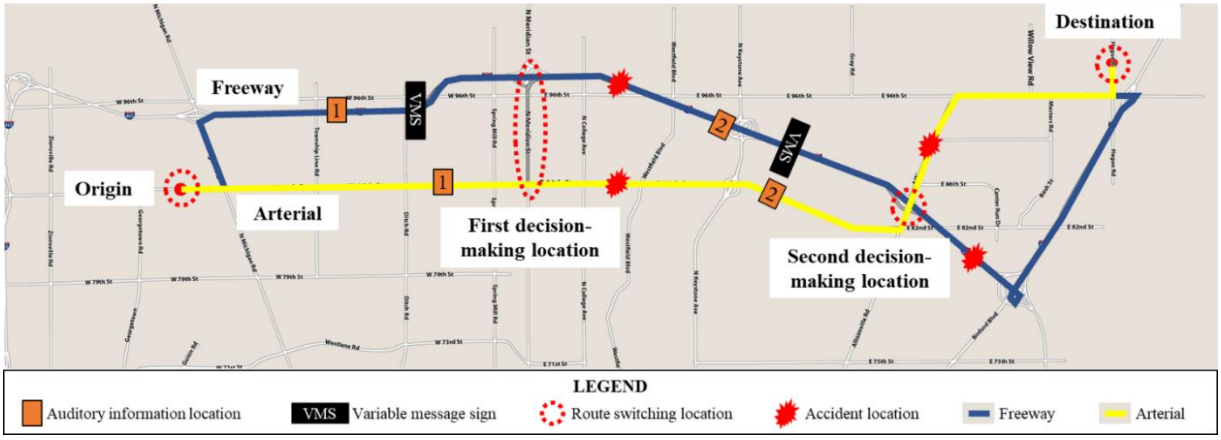

Figure 2 Experiment roadmap illustrating real-time information provision locations

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 about the alternative route or route recommendation. PI is available only in scenarios with road accident. The same information is also provided on a smartphone afterwards in case drivers do not understand the auditory information. The scenarios also had provision for visual real-time travel information on freeways via variable message sign (VMS) which is located after the auditory information provision location. This study only uses data near first information provision location (marked as '[1]' in **Figure** 2) to mitigate the effects of VMS and avoid the interaction effects with multiple real-time

information in a single trip. The real-time auditory travel information provided to the participants in this experiment are presented in Table 1.

Figure 3 Driving simulator equipment

Table 1 presents the real-time auditory travel information that was provided to drivers under four information scenarios via personal device on the freeway and arterial routes for two traffic congestion scenarios.

Table 1. Real-Time Auditory Travel Information that was provided to Drivers

Scenario	Accident	Current Route	
		Freeway	Arterial
NI	Yes/No	-	-
CT	No	Travel time to destination via I-465 & I-69 is 19 minutes	Travel time to destination via 86th Street & Allisonville road is 25 minutes
	Yes	Travel time to destination via I-465 & I-69 is 27 minutes	Travel time to destination via 86th Street & Allisonville road is 35 minutes
AT	No	Travel time to destination via I-465 & I-69 is 19 minutes; via 86th Street & Allisonville Road is 16 minutes	Travel time to destination via 86th Street & Allisonville road is 25 minutes; via I-465 & I-69 is 14 minutes
	Yes	Travel time to destination via I-465 & I-69 is 27 minutes; via 86th Street & Allisonville road is 22 minutes	Travel time to destination via 86th Street & Allisonville road is 35 minutes; via I-465 & I-69 is 20 minutes
PI	No	-	-
	Yes	Congestion ahead. Take 86th Street & Allisonville Road	Congestion Ahead. Take I-465 & I-69

2.3. Participants

Participants were recruited from the community through advertisements in a university-wide email newsletter, paper fliers, and word of mouth. The following inclusion criteria is used to recruit participants: (1) being 18 years of age or older, (2) having a valid driver's license, (3) do not wear corrective glasses (as we also collected eye tracking data), (4) no predisposition to motion sickness, and (5) no self-reported physical or mental impairments. All recruited participants self-reported no medication or caffeine ingestion for at least 8 hours prior to the experiment. Participants signed up for the experiment through the experiment website.

Participants were asked to drive three times in the simulator with randomly assigned information scenarios. Participants were compensated (with a maximum of $60) based on a point-based reward system that emulates their intent to complete the trip within assigned time limit and observe all traffic rules. All participants were instructed to drive as if they are commuting to work. A basic level of familiarity with the road network and information sources was created for all the participants in the practice run during the introduction phase. 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 25 minutes. Then, participants were asked about their preferred route and a fast-forwarded driving video of that route with several pauses to emphasize important sign boards and turns was shown to the participants to enhance their familiarity with that route. 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 ± 7.0 years) as illustrated in Figure 4. Figure 5 illustrates the distribution of information scenarios grouped by the traveled route at the first information provision location for all experiment runs.

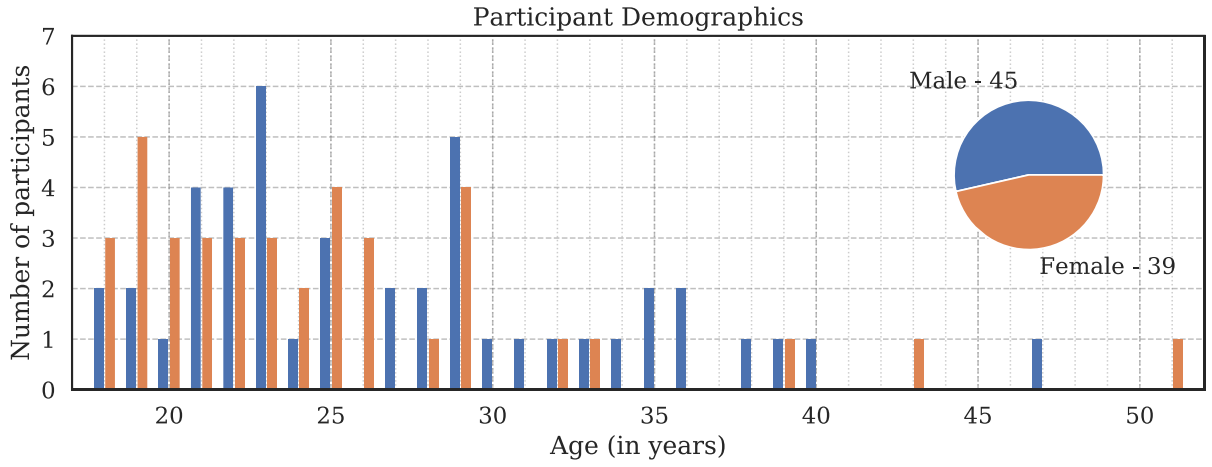

Figure 4 Participant age and gender distribution

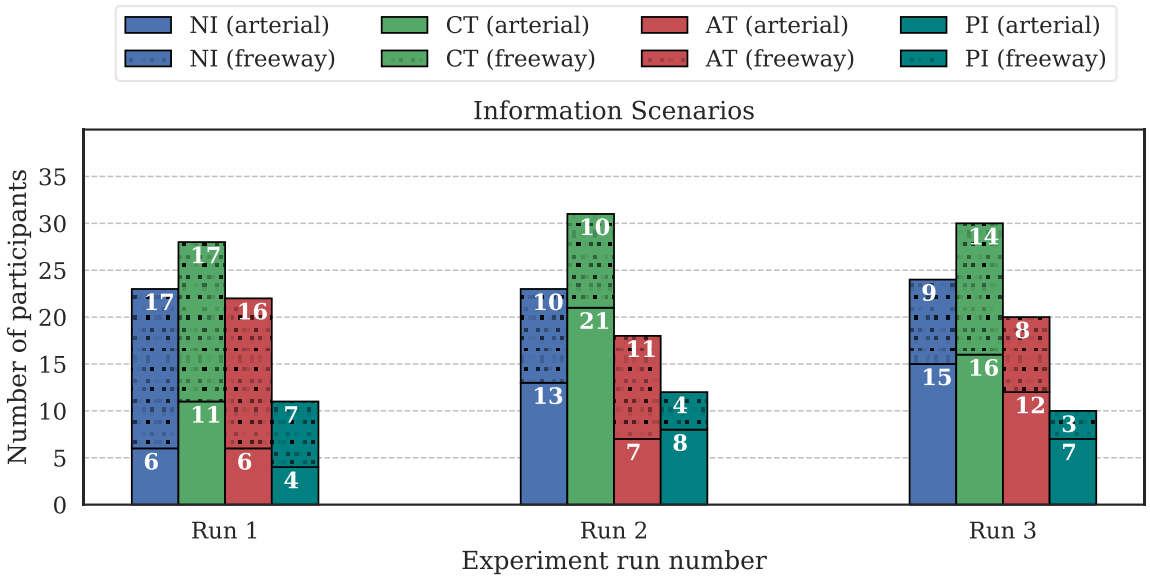

Figure 5 Information scenario distribution by route and experiment run

2.4. Electroencephalogram (EEG)

Drivers' brain electrical activity data is collected using B-Alert X24 EEG system (Advanced Brain Monitoring, 2017). The EEG electrodes (or 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 presented in Table 2. The mastoids are used as a reference for measuring electrical signal. The data is collected with a sampling rate of 256 Hz.

Table 2 Brain regions and corresponding EEG channels

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

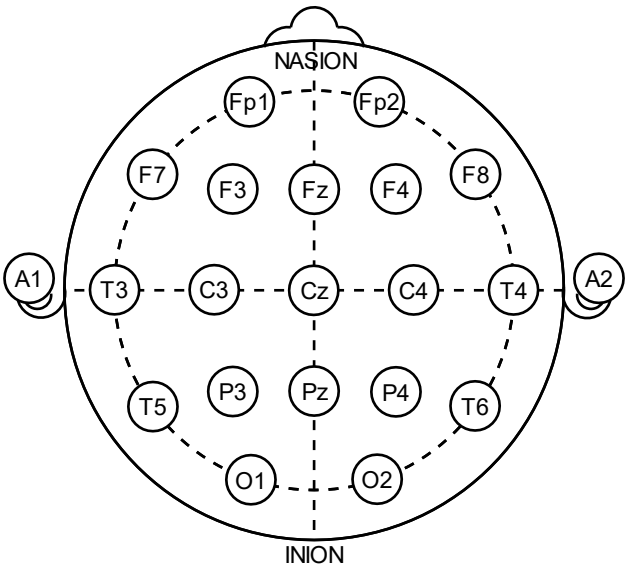

Figure 6 EEG electrode locations as per International 10-20 System

Prior to data analysis, raw EEG signal is processed to remove contaminations (also known as *artifacts*). ABM'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). 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, PSD for each epoch is averaged over 3 epochs by applying 50% overlapping window to smooth the data. This study analyzes the EEG power within four frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz) and beta (13-30 Hz). The band powers are calculated by averaging the PSD within respective frequency bandwidth. Four time windows around 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.

In the context of EEG frequency bands, each band is associated with certain cognitive state or activity. For example, beta band power is higher during anxiety, stress, problem solving and focused attention, while alpha band power increases with inability to focus and relaxed state of mind, and decreases with focused attention or anxiety (Abhang et al., 2016b). High theta band power is often associated with drowsiness and fatigue (Craig et al., 2012; Klimesch, 1999), but could also increase with increase in task demand related to attention, memory and affective processing (Golocheikine and Aftanas, 2001). High delta band power is the main characteristic of sleep, but can also occur during increased attention to internal processing or memory retrieval in a wakeful state by temporarily suppressing non-relevant neural activity (external perception) (Harmony, 2013; Harmony et al., 1996).

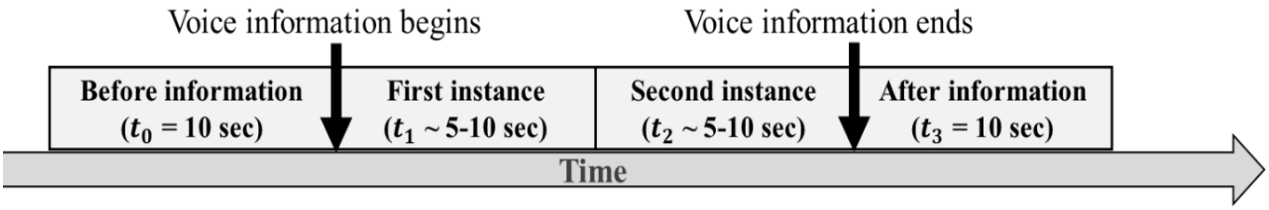

Figure 7 Time windows near information provision location

2.5. Data Analysis

Linear mixed models (LMMs; also known as *multilevel models*) are used to analyze the difference in band powers for each EEG channel (19 channels), EEG band (4 bands), run (3 runs), and route (2 routes). In contrast to simple linear models, LMMs can analyze data with non-independent or correlated errors due to the underlying hierarchical structure (such as repeated measurements from same participant) in the data. 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 information scenarios, time windows and their interactions. Band powers in multiple time windows for each participant are modeled as normally-distributed random effects. No information (NI) scenario and pre-information time period t_0 are chosen as references for information scenarios and time windows, respectively.

The basic model form is as follows:

$$\text{bp} \sim \beta_0 + \beta_{\text{info}} + \beta_{\text{time}} + \beta_{\text{info}*\text{time}} + \gamma_{\text{participant}} + \varepsilon,$$

where:
bp denotes the band power as dependent variable,
β_0 the intercept, β_{info} the coefficient for information scenario,
β_{time} the coefficient for time window,
$\beta_{\text{info}*\text{time}}$ the interaction effects coefficient for information scenario and time window,
$\gamma_{\text{participant}}$ the random effects for participant repeated measures, and
ε the normally distributed error term.

The experiment scenarios are designed to create similar ambient traffic conditions within the analysis time boundary (i.e., the four time periods near information provision location) on specific route. Although micro-level traffic interactions can contribute to unwanted noise in the model, this study deliberately allows free interactions with the ambient traffic for analyzing EEG data in realistic driving conditions to enhance ecological validity. Moreover, the choice of NI and t_0 as references allow the analysis of information impacts on drivers while segregating the effects of systematic route characteristics (e.g., road curvature, traffic lights, etc.) and macro-level traffic conditions to some extent.

3. RESULTS AND DISCUSSION

The LMM results for freeway and arterial routes are illustrated in Figure 8 and Figure 9, respectively, as *brain-maps*. The brain-maps in the first row (i.e., NI-t_1, NI-t_2 and NI-t_3) and first column (i.e., CT-t_0, AT-t_0 and PI-t_0) represent the main effects of time stages of interaction and information scenarios, respectively, while other brain-maps represent their interaction effects. The colormap indicates the change in band powers due to main effects and interaction effects, with red indicating positive coefficient and blue indicating negative coefficient. The statistical significance level of 99% and 95% are represented by solid circle and hollow circle, respectively, in the figures. The model intercepts denote the baseline brain-maps (i.e., NI-t_0) and are not shown in the figures as their values are significantly higher than the effects.

Since the participants do not have any prior experience with or expectation of information provision in the first experiment run, the observed systematic differences in EEG band power are most likely caused by route-specific features (e.g., sign boards and road curvature) and ambient traffic conditions. These differences are illustrated by the run 1 model coefficients of NI scenarios (i.e., NI-t_1, NI-t_2 and NI-t_3 brain-maps) for both freeway and arterial routes. As illustrated in Figure 8, there are little-to-no differences in EEG band power on freeway. The slight decrease in delta and theta band powers, especially in sensory regions of the brain (i.e., temporal and occipital regions), suggest systematic impacts of driving environment (i.e., road characteristics and traffic interactions) near information provision location. This reasoning is further supported by the significantly higher differences in band powers on arterial as illustrated in Figure 9, which has a more complex driving environment than freeway. The steadily decreasing delta and theta band powers over time in frontal region on arterial suggest diminishing memory retrieval or attention that arise from driver interaction with road objects (e.g., street name sign or traffic signal) during time period t_0. This is consistent with the experiment road network as the information provision location is immediately after an intersection comprising of several road objects (as illustrated in **Figure** 2). These results indicate that the driving environment near information provision location affects EEG patterns.

The results illustrate that delta and theta band powers increase with time on arterial in run 1, mainly in left frontotemporal region, under all three information scenarios (CT, AT and PI) which could be a result of increased attention to internal processing (Harmony, 2013) as well as memory retrieval processing (Golocheikine and Aftanas, 2001) after receiving real-time travel information. Further, this increase is more pronounced on CT compared to AT and PI. This suggests that insufficient information under CT, that is, lack of travel time information on alternative route or any specific route recommendation, results in higher cognitive task demand (memory retrieval and internal processing). On freeway, delta and theta powers mostly remain unchanged under CT, while slightly increased under AT and PI. This suggests that drivers most likely had to spend lower cognitive effort to process information on freeway compared to arterial, especially under insufficient information. Furthermore, the revealed route choices in run 1 shows that among drivers traveling on arterial, 3 out of 6 drivers under NI, 1 out of 11 under CT, 0 out of 6 under AT and 0 out of 4 under PI chose to continue on arterial after the first decision-making location. In contrast, 13 out of 17 drivers under NI, 12 out of 15 under CT, 7 out of 16 under AT and 0 out of 7 under PI stayed on freeway. Two key observations can be made from these revealed route choices: (i) most drivers on arterial switched their route under information provision, and (ii) all drivers

followed the route recommendation under PI in run 1. The first observation is consistent with the fact that travel time uncertainty is typically higher on arterial routes than freeway due to the presence of traffic signals and more complex traffic interactions (Billings and Yang, 2006), which may have affected route switching decision. While the second observation suggests greater driver compliance with route recommendation in unfamiliar travel environment.

Alpha band power is mostly unchanged in run 1, except an initial decrease followed by an increase in the temporal and occipital region under AT and PI on arterial. Lower alpha waves are associated with increased conscious effort and anxiety, while higher alpha waves represent a relaxed state (Abhang et al., 2016b). This suggests that drivers require more conscious effort during information perception due to either more amount of information units, or negative information content in their travel context ("congestion ahead" under PI), which gradually decreases post-information (t_3). This is also evident with lower beta power under CT and AT on arterial, which could manifest from driving distraction under semantic task (Almahasneh et al., 2014) such as information perception. The slightly higher decrease in beta power under AT compared to CT on arterial, and little-to-no change on freeway also suggests that the level of driver distraction under real-time travel information provision does not only depend on the amount of information (AT has twice the information amount as CT), but also the complexity of the driving environment (arterial is more complex than freeway). On the other hand, the significant increase in beta band power on freeway under PI during t_2 and t_3 suggests higher anxiety and increased arousal (Abhang et al., 2016b; Morales et al., 2017) among drivers due to the recommended route switch from freeway to arterial. Even though it is easier for the drivers to perceive and process information on freeway (as discussed earlier), the unfavorable information content resulting in a seemingly difficult route choice decision can induce anxiety.

Several intermediate learning effects can be observed in run 2 where participants either overreact or underreact to the real-time information. For example, the mostly unaffected delta and theta band powers under NI suggest reduced impacts of route and traffic characteristics, possibly due to the inattention towards driving environment caused by anticipation of real-time information. The reduced alpha activity on arterial under NI can be caused by increased alertness (Golocheikine and Aftanas, 2001) and simple memory tasks (Harmony, 2013), such as pinpointing the information provision location from recognizable landmarks on arterial. Higher beta activity on freeway under NI suggests increased drivers' attention to external stimuli in anticipation of information and possible increase in anxiety when the information is not received. The slight increase in theta band power under CT on arterial does suggest higher task demand (e.g., memory retrieval) in case of insufficient information, but overall, the effects of information are minimal on band powers on the arterial route in run 2. The increase in theta band power under PI on freeway suggests that attentional and memory task demand increases when descriptive travel time is not provided. The excessive decrease in alpha and beta band powers under CT and PI suggests increased conscious effort, most likely due to precognition as a result of increasing familiarity with the experiment process, and lower anxiety. Premeditated decision could also be the cause of lower anxiety, as 3 out of 4 participants driving on freeway stayed on freeway under PI in run 2 compared to 0 out of 7 in run 1. Overall, the current experiment design limits the ability to make concrete inferences for the second experiment run because of the overlapping presence of learning effects with the equipment (i.e. driving simulator), road network and information sources.

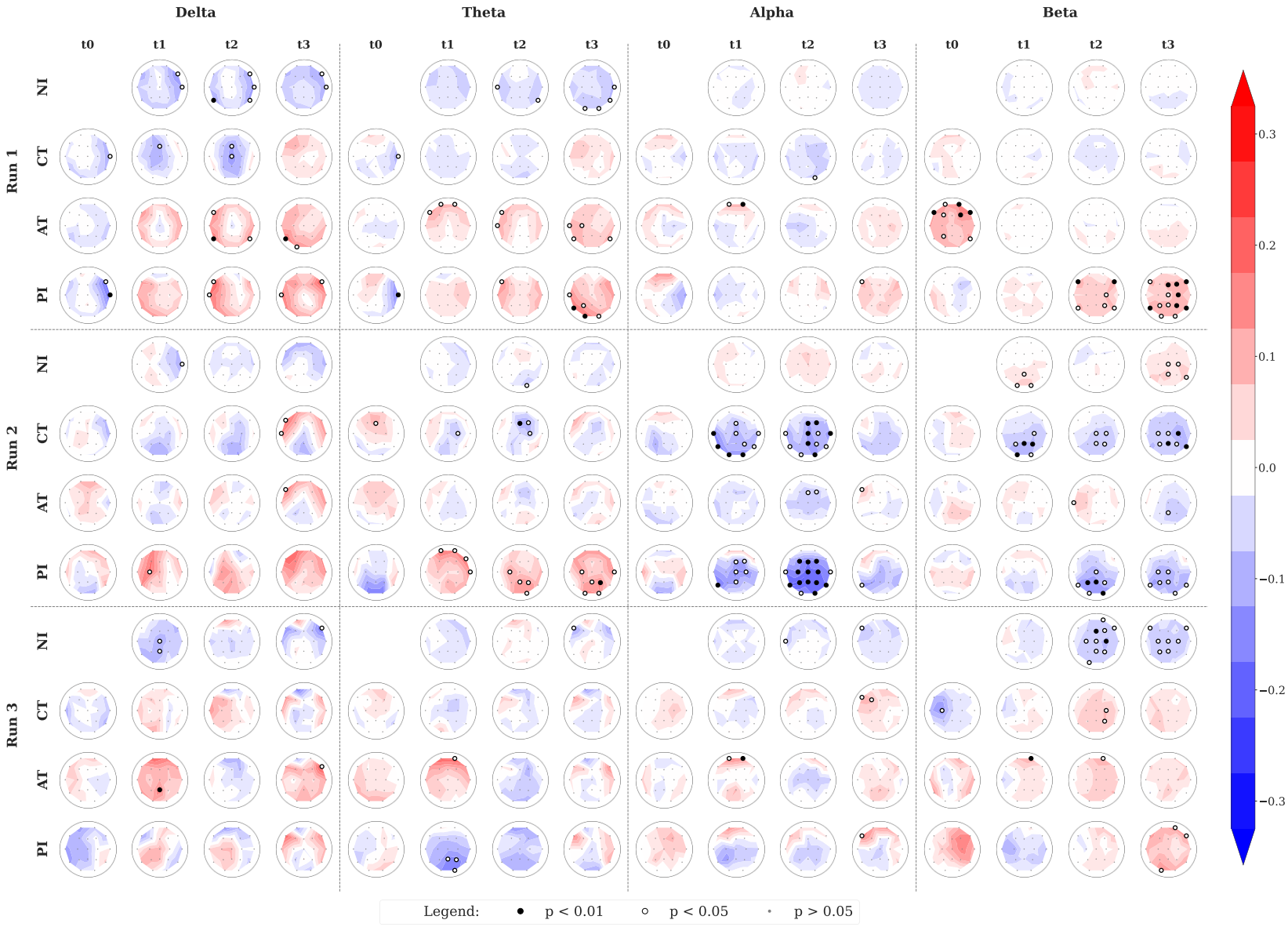

Figure 8 Linear mixed model results for the freeway route

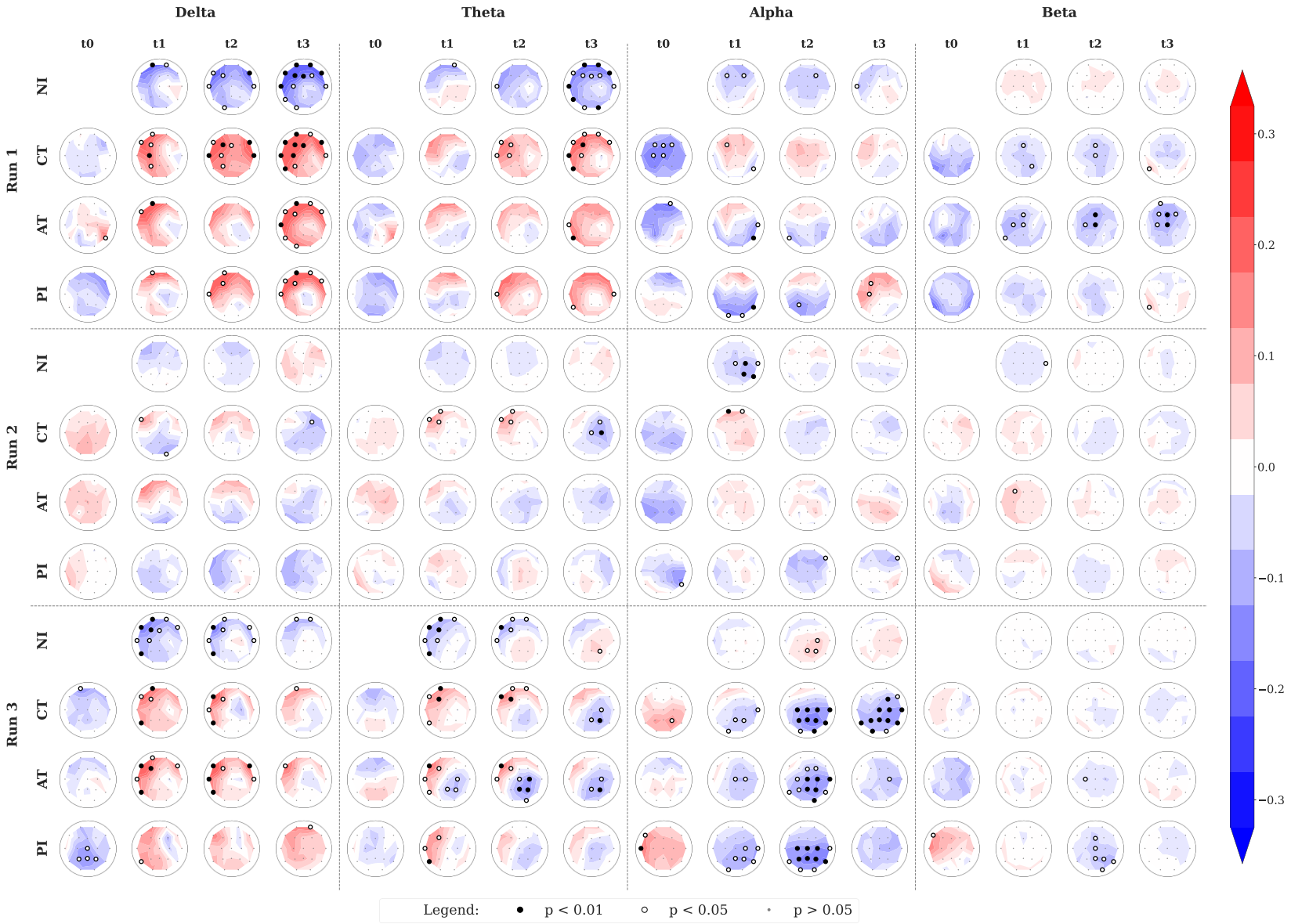

Figure 9 Linear mixed model results for the arterial route

The final run is characterized by the combined impacts of driver fatigue (as participants have spent almost 2 to 2.5 hours in the laboratory including around 1 to 1.5 hours of simulator driving), drowsiness, increased overall familiarity with the driving environment, and the "end-spurt" effect that occurs when the participants know that the experiment is in its final stage (Morales et al., 2017). On the arterial route, the delta and theta band power in run 3 under NI shows a similar decrease after the information provision location as in run 1, but with reduced magnitude and opposite temporal evolution pattern. This could be due to faster recognition of road characteristics with increased familiarity.

A similar effect is observed under descriptive information scenarios (CT and AT) as well where the delta and theta band power in the left frontotemporal region is prominent similar to run 1, but decreases with time unlike run 1. This suggests a quicker memory retrieval of experiential information which could be attributed to increased accessibility to relevant information from repeated driving tasks in the same traffic network in a short period of time. The reduced theta power in the parietal region under AT and CT could be a result of reduced drowsiness after the auditory information provision (during t_1, t_2 and t_3). More focused experiments can be designed in the future to analyze the cognitive and psychological impacts of real-time information provision under driver fatigue.

The widespread decrease in alpha band power under information provision on arterial in run 3 indicates a more conscious effort for information perception and processing. This suggests that increase in familiarity with complex driving environment may allow drivers to spend more cognitive resources on real-time information by reducing cognitive load due to driving itself. The results illustrate almost no interaction effects of time and information on EEG band powers on freeway in run 3.

4. CONCLUDING COMMENTS

This research focuses on evaluating the cognitive and psychological effects of auditory real-time travel information on drivers from the perspective of neurophysiology and driver route choice behavior. EEG is used to measure brain electrical signals of the drivers in a driving simulator environment with a network-level roadmap. Drivers can choose between two routes, arterial and freeway, to reach their destination. A point-based reward system, which incentivizes drivers for reaching the destination on time and penalizes rash driving behavior such as over-speeding, is employed to mimic realistic route choice behavior. Further, a microscopic traffic simulator is integrated with the driving simulator to generate responsive ambient traffic. Four auditory information scenarios with varying information characteristics (amount and content) are created to provide drivers with real-time travel information prior to making route choice decisions.

The differences in frequency band powers of the EEG signals near the information provision location with respect to information characteristics and time stages of interaction with information (i.e., before, during and after information provision) are analyzed using linear mixed models. A detailed account of the model results is presented in the previous section. Three key inferences can be made from the results.

First, information perception and processing while driving on a route with several roadside objects and complex traffic interactions require more cognitive resources. Thus, providing real-time auditory information, such as from smartphones, in such driving environments could pose a risk to driver safety by distracting them from their primary driving task.

Second, insufficient real-time travel information can result in higher cognitive task demand, particularly when traveling on routes characterized by high travel time uncertainty. But at the same time, perceiving and processing more information requires more conscious effort from the drivers. Future research can focus on analyzing such impacts and designing information systems to provide the optimal amount of information to drivers under different driving environments while managing distraction.

Third, the recommendation to switch to a more complex route with higher travel time uncertainty (i.e., freeway to arterial in this study) can cause higher anxiety in drivers compared to its counterpart. Driving under anxiety and stress have been known to deteriorate driving performance and, thereby, negatively affect the driver's safety. Therefore, redesigning information content alongside information amount is just as important for better, and potentially safer, information systems from the perspective of driver cognition. These inferences can aid in improving future real-time information systems.

The study limitations are as follows. First, the sample population consists mainly of millennials who are university students, which means that the results may not reflect the behavior of general population. Second, the interaction effects of routes and runs are ignored as they are modeled separately due to limited sample size with valid EEG data. In future studies, such interaction effects can be captured with focused experiment design and larger sample size. Third, the experiential and learning effects of other information sources (i.e., VMS and second information provision) on run 2 and run 3 are ignored. Also, the familiarity with equipment, road network and information sources are assumed to depend only on the number of prior driving runs, when in reality route choices and experienced information scenario may affect the participant's level of familiarity. Possible future research directions may include developing hybrid driver behavior models with

driver physiological data under real-time information provision, evaluating other characteristics of real-time travel information (e.g., source and modality), analyzing the impacts of driver fatigue on real-time information perception/processing and route choice decision-making behavior, and developing an integrated real-time information system and driver monitoring system to provide information based on driver's psychophysiological state.

5. SYNOPSIS OF PERFORMANCE INDICATORS

The research from this was advanced. The research from this project was disseminated to 145 people from industry, government, and academia at several conferences, including the 2017 INFORMS Annual Meeting in Houston, Texas, 2018 International Conference on Travel Behavior Research in Santa Barbara, California, 2018 INFORMS Annual Meeting in Phoenix, Arizona, 2019 INFORMS Annual Meeting in Seattle, Washington, and 2019 International Conference on Applied Human Factors and Ergonomics, Washington D.C. This project supported 2 students at the doctoral level.

Research Performance Indicators: 9 conference and workshop articles and 1 peer-reviewed journal article were produced from this project.

The outputs, outcomes, and impacts are described in the following sections.

6. OUTPUTS, OUTCOMES, AND IMPACTS

6.1. List of research outputs (publications, conference papers, and presentations)

- Agrawal, S., & Peeta, S. (2021). Hybrid route choice model incorporating latent cognitive effects of real-time travel information using physiological data. Transportation Research Part F: Traffic Psychology and Behaviour, 81, 223–239. https://doi.org/10.1016/j.trf.2021.05.021
- Agrawal, S., & Peeta, S. (January 2021). Hybrid route choice model incorporating latent cognitive and psychological effects of real-time travel information using physiological data [Poster presentation]. 100th Annual Meeting of the Transportation Research Board (TRB), virtual.
- Agrawal, S., Benedyk, I., & Peeta, S. (October 2019). Evaluating the impacts of real-time travel information on driver physiology [Paper presentation]. INFORMS Annual Meeting, Seattle, WA.
- Agrawal, S., Benedyk, I., & Peeta, S. (July 2019). Evaluating the impacts of real-time auditory travel information provision on driver cognition using EEG spectrum analysis [Paper presentation]. 10th International Conference on Applied Human Factors and Ergonomics (AHFE), Washington, D.C.
- Agrawal, S., Benedyk, I., & Peeta, S. (March 2019). Modeling driver physiological state using EEG under auditory real-time travel information provision [Poster presentation]. 105th Purdue Road School Transportation Conference and Expo, Purdue University, West Lafayette, IN.
- Agrawal, S., Benedyk, I., & Peeta, S. (February 2019). Modeling driver physiological state using EEG under auditory real-time travel information provision [Poster presentation]. Autonomous Vehicles Workshop organized by Institute for Pure & Applied Mathematics (IPAM), University of California, Los Angeles, CA.
- Agrawal, S., Benedyk, I., & Peeta, S. (November 2018). Evaluating the cognitive effects of real-time travel information using psychophysiological analysis and their implications for driver decision-making [Paper presentation]. INFORMS Annual Meeting, Phoenix, AZ.
- Agrawal, S., Benedyk, I., Peeta, S. (presenter), & Song, D. Y. (July 2018). Evaluating driver cognitive state under real-time travel information provision using physiological factors and its impacts on route choice behavior [Paper presentation]. 15th International Conference on Travel Behavior Research (IATBR), Santa Barbara, CA.
- Agrawal, S., Benedyk, I. (presenter), & Peeta, S. (March 2018). Evaluating the cognitive effects of real-time travel information using physiological indicators [Poster presentation]. 2018 Global Symposium on Connected and Automated Transportation and Infrastructure, Ann Arbor, MI.
- Agrawal, S., Benedyk, I., D. Song, & Peeta, S. (October 2017). Quantifying impacts of real-time

travel information on route choice behavior using psychophysiological analysis: A driving simulator-based study [Paper presentation]. INFORMS Annual Meeting, Houston, TX.

6.2. Outcomes

This project advances the understanding of real-time information systems on driver's latent cognition and psychology. These latent aspects are explicitly measures and evaluated using physiological data (brain electrical activity) measured by an electroencephalogram (EEG). Thus, it overcomes the potential memory biases associated with existing survey-based instruments to analyze cognitive and psychological effects of information. By collecting data in a driving simulator with realistic network-level driving environment and responsive ambient traffic, this research enhances the ecological validity of the findings.

6.3. Impacts

Real-time information has significantly become more complex, diverse, and ubiquitous in recent years. Drivers now have access to real-time information from a variety of sources. Although more information enables drivers to make more informed travel decisions, poorly designed en route information can lead to negative cognitive and psychological implications for drivers (e.g., driver distraction). This project investigates the cognitive and psychological effects of real-time information in driving simulator environments using objective physiological data, which allows overcoming certain limitations of survey-based instruments (e.g., memory biases). Study results can aid real-time information providers (private and public) and auto manufacturers to incorporate the latent cognitive and psychological effects of information in designing real-time information and its delivery systems for improving road safety and user experience. From the perspective of traffic operators, an understanding of driver cognition and psychology under information can help improve route choice behavior models under information provision to better predict and subsequently manage traffic conditions.

6.4. Tech Transfer

In the execution of this project, the research team undertook a number of technology transfer activities. First, the research team published one article in a technical journal with a wide readership, high reputation, and high impact factor. The team also presented the project research to a diverse group of audience at multiple conferences. Further, a number of tech transfer activities were undertaken as part of this project, such as communication with other universities through webinars and forums. These tech transfer activities undertaken by the research team through the course of this project are listed in Section 6.1.

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APPENDIX: JOURNAL PAPERS PUBLISHED FROM THIS WORK

CCAT Project Title: Development of In-vehicle Information Dissemination Mechanisms to Reduce Cognitive Burden in the Information-rich Driving Environment

Agrawal, S., Peeta, S. (2021). Hybrid route choice model incorporating latent cognitive effects of real-time travel information using physiological data, Transportation Research Part F: Traffic Psychology and Behavior 81(1), 223-239.

Abstract:

The proliferation of information systems is enabling drivers to receive en route real-time travel information, often from multiple sources, for making informed routing decisions. A robust understanding of route choice behavior under information provision can be leveraged by traffic operators to design information and its delivery systems for managing network-wide traffic. However, most existing route choice models lack the ability to consider the latent cognitive effects of information on drivers and their implications on route choice decisions. This paper presents a hybrid route choice modeling framework that incorporates the latent cognitive effects of real-time information and the effects of several explanatory variables that can be measured directly (i.e., route characteristics, information characteristics, driver attributes, and situational factors). The latent cognitive effects are estimated by analyzing drivers' physiological data (i.e., brain electrical activity patterns) measured using an electroencephalogram (EEG). Data was collected for 95 participants in driving simulator experiments designed to elicit realistic route choices using a network-level setup featuring routes with different characteristics (in terms of travel time and driving environment complexity) and dynamic ambient traffic. Averaged EEG band powers in multiple brain regions were used to extract two latent cognitive variables that capture driver's cognitive effort during and immediately after the information provision, and cognitive inattention before implementing the route choice decision. A Multiple Indicators Multiple Causes model was used to test the effects of several explanatory factors on the latent cognitive variables, and their combined impacts on route choice decisions. The study results highlight the significant effects of driver attributes and information characteristics on latent cognitive effort and of route characteristics on latent cognitive inattention. They also indicate that drivers who are more attentive and exert more cognitive effort are more likely to switch from their current route by complying with the information provided. The study insights can aid traffic operators and information service providers to incorporate human factors and cognitive aspects while devising strategies for designing and disseminating real-time travel information to influence drivers' route choices.