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Driving Simulator Based Interactive Experiments: Understanding Driver Behavior, Cognition and Technology Uptake under Information and Communication Technologies

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DISCLAIMER

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TECHNICAL SUMMARY

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Title

Driving Simulator Based Interactive Experiments: Understanding Driver Behavior, Cognition and Technology Uptake under Information and Communication Technologies

Introduction

Advanced Traveler Information Systems (ATIS) and in-vehicle information systems (IVIS) are becoming an integral part of the current driving experience. Although information through in-vehicle technologies provides assistance to drivers with diverse travel-related information (for example, real-time traffic information, weather forecast, and warning and emergency alerts), it also entails additional cognitive workload that can cause safety hazards and behavioral inconsistencies, especially if the information delivery mechanism is not well-designed. Thus, understanding the impacts of real-time information from multiple sources (such as variable message signs, GPS, radio, etc.) on drivers' cognition and its effects on the decision-making process is essential for designing futuristic IVIS. In addition, it is desired that a driver would fully comply with such information to improve transportation system performance.

In this study, we develop interactive driving simulator experiments to understand the relationship of drivers' physiological data on their perceptional and psychological states as well as their revealed route choices. These experiments use a real road network from Indianapolis, Indiana, for which participants determine route preferences based on real-time information provision as well as route attributes (e.g., freeway, number of turns, stops, length, and so on). Various information scenarios with multiple disseminating sources are prepared to examine participants' perceptional and psychological states depending on different information characteristics (e.g., amount, source, or content). High-definition cameras and biosensors (i.e., electroencephalography, electrocardiography, and eye tracker) are integrated with the driving simulator experiments to observe participants' physiological data. The real-time coordination between the multiple biosensors, high-definition cameras, and driving scenarios enables to understand drivers' dynamic cognitive states during the driving period depending on the presented cues (such as real-time travel information). Based on the data collected, we develop behavior models to investigate the impacts of cognitive effects induced by real-time traffic information along with situational factors (such as trip purpose and traffic congestion), real-time travel information characteristics (such as amount, content and source) and individual driver characteristics (such as age, gender and education) on the driver route choice decision-making process.

Findings

The key findings are as follows: (i) the stress from information overload or information-induced confusion can weaken the influence or effectiveness of information to alter travelers' route choice; (ii) if travelers have more clarity on the ambient traffic conditions on the alternative route (higher cognitive decisiveness), they are more likely to choose it when it has better traffic conditions; and (iii) if a traveler feels the information is favorable (for example, available alternative route has a lower expected travel time), he/she would switch to that route.

The key contributions of this project are: (i) demonstrating the causal relationships among the factors that lead to the psychological effects of real-time travel information, (ii) explicitly eliciting the latent psychological factors from drivers' revealed behavior to understand the holistic structure of the benefits of real-time travel information, and (iii) quantifying the driver cognitive state and workload using physiological data acquired from biosensors (such as electroencephalography, electrocardiography, and eye tracker) using the carefully designed interactive driving simulator experiments.

Recommendations

The results illustrate the effectiveness of using data from the interactive driving simulator experiments designed in this study to understand the multiple dimensions of driver response behavior under real-time information provision, beyond those linked to travel time savings. The study results also demonstrate the efficiency of using biosensors to infer on driver cognitive states. Based on the surveys and biosensors used in this study, the qualitative and psychological implications of information can be analyzed by seamlessly collecting information that can enable revealing the causal relationships and factors. The use of an interactive driving simulator has practical merits compared to conducting driving experiments on a public road network. First, it provides flexibility to build a variety of scenarios in terms of network characteristics (highway geometry and road surface characteristics), information characteristics (amount, sources, and content), and travel context (demand levels, accidents, and weather conditions). Second, it is safer and entails much lower risk than field experiments. Third, it enables controlling for factors so that understanding the role of specific factors can be analyzed. The study insights can aid vehicle manufacturers to design IVIS and transportation planners to develop strategies that reduce cognitive workload for real-time travel information provision and enhance the effectiveness of travelers' route choice decision-making behavior by incorporating the psychological effects of real-time travel information provision.

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CHAPTER 1. INTRODUCTION

1.1 Background and motivation

Real-time travel information provision under Advanced Traveler Information Systems (ATIS) can significantly impact network traffic flow evolution by influencing drivers' route choice decisions. Recent advances in information and mobile communication technologies have enabled the delivery of real-time information through personal devices (for example, smartphones) and in-vehicle information systems (IVIS) (for example, integrated navigation system and vehicle dashboard). These systems, unlike public information infrastructure (for example, variable message sign and roadside sign boards), can provide personalized real-time travel information to drivers. Thus, drivers can receive both travel-related information (for example, route navigation, real-time traffic information, weather forecast, and collision warning and emergency alerts) and non-travel related information (for example, phone calls, emails and vehicle diagnostics) through multiple sources at different times and locations, and in different sensory modalities (for example, visual, auditory and tactile) and formats (for example, text, image, verbal, non-verbal alert sounds and vibration). Real-time travel information enables drivers to make informed travel decisions (for example, route choice) that have tangible (for example, travel time savings) and cognitive (for example, cognitive decisiveness and emotional relief) benefits. But, it also may have negative implications on driver cognitive states during perception and processing of information as it entails sharing of cognitive resources while engaged in the multitasking driving activity.

The impacts of real-time travel information on driver behavior related to mode choice, departure time choice and route choice have been well-studied in the literature (Dia, 2002; Grotenhuis, Wiegmans, & Rietveld, 2007; Peeta & Yu, 2004; Thorhauge, Haustein, & Cherchi, 2016; Yu & Peeta, 2011). Several studies have investigated the day-to-day and within-day evolution of driver behavior and flow in traffic networks (L. Han, Sun, Wu, & Zhu, 2011; Jha, Madanat, & Peeta, 1998), and its impacts on transportation network performance (Mahmassani & Jayakrishnan, 1991). Some studies have shown the benefits of IVIS to improve driver's situational awareness, and avoid fatigued and drowsy driving (Gershon, Ronen, Oron-Gilad, & Shinar, 2009; Nijboer, Borst, van Rijn, & Taatgen, 2016). However, driving is inherently a multitasking activity that requires drivers to perform essential functions (for example, steering, accelerating and braking) while interacting with the travel environment. The provision of real-time information can result in cognitive overload which can jeopardize drivers' performance, both in terms of driving and information processing. Previous literature has shown that interacting with information systems while driving increases driver's cognitive workload that can reduce the effectiveness of the disseminated information which subsequently affects the route choice decision-making process, and cause distraction that can result in negative safety implications (Birrell & Young, 2011; Dong, Hu, Uchimura, & Murayama, 2011; Jamson & Merat, 2005; Ranney, Scott Baldwin, Smith, Martin, & Mazzae, 2013; Briggs, Hole, & Land, 2016). In addition, several inconsistencies in information may arise due to the difference in information characteristics from multiple sources (for example, delivery format, content, and latency) that can result in information-based confusion in the context of the route choice decision-making process. Real-time information available under connected and autonomous transportation technologies may further aggravate the information overload of drivers, if the technology developers and information providers fail to consider the cognitive capabilities of human drivers while designing information dissemination strategies. Hence, it is imperative to investigate the impacts of real-time travel information on driver cognition, and consequently driver route choice behavior.

Most of the proposed route choice behavior models in the literature incorporates road/route characteristics (such as road type), experiential generalized travel costs (such as experienced travel time and fuel consumption), population heterogeneity in terms of individual factors (such as sociodemographic characteristics, trip purpose), and real-time information (Agrawal, Zheng, Peeta, & Kumar, 2016; P. Bonsall, 1992; Dia, 2002; K. Han, Friesz, & Yao, 2013; Peeta & Yu, 2005; Yu & Peeta, 2011). Some studies have also shown the impacts of the accuracy of information (Ben-Elia, Di Pace, Bifulco, & Shiftan, 2013), content of information (Peeta, Ramos, & Pasupathy, 2000) and past experience with information (Ben-Elia, Erev, & Shiftan, 2008) on driver route choice behavior. Hato et al. (1999) studied the route choice behavior under provision of real-time travel information through multiple information sources. Several studies have also analyzed the compliance of drivers towards real-time travel information (Chen, Srinivasan, Mahmassani, Engineering, & Jr, 1999; Srinivasan & Mahmassani, 2000), and the value of real-time travel information for the drivers (Chorus, Arentze, Molin, Timmermans, & Van Wee, 2006; Kim & Vandebona, 1999; Levinson, 2003; Zhang & Levinson, 2008). Past literature has also studied the effects of timing of information provision on drivers' route choice behavior, that is, pre-trip information (Jou, 2001; Khattak, Polydoropoulou, & Ben-Akiva, 1996), en route information (Srinivas Peeta & Yu, 2005; Polydoropoulou, Ben-Akiva, Khattak, & Lauprete, 1996), and post-trip information (Lu, Gao, & Ben-Elia, 2011). However, most of the proposed driver route choice behavior models that include the effects of real-time travel information (for example, Peeta and Yu, 2005) are limited in their capability to factor human cognition, and assume that drivers are able to seamlessly perceive, process and utilize real-time information while performing an already cognition-heavy driving task (Ben-Elia & Avineri, 2015).

In terms of qualitative aspects of information perception, Bonsall (2004) and Chorus et al., (2006b) show that traveler route choice decisions rely on the subjective perception of the provided information associated with traveler attributes and situational factors. That is, even if the same information is provided to travelers under similar traffic conditions, their route choice decisions may differ because the information is perceived and used differently by different travelers. Following this thread, different approaches have been used to study the effects of real-time travel information by factoring the qualitative aspects of information perception. For instance, well-defined behavioral theories on the limitations or distortions in human cognition and reasoning, such as bounded rationality (Gao, Frejinger, & Ben-Akiva, 2011), prospect theory (Razo & Gao, 2013), and regret theory (Chorus, Arentze, & Timmermans, 2008), are leveraged to develop modeling structures that account for the qualitative aspects of travelers' behavioral responses to real-time travel information. However, an underlying assumption in these studies is that travelers can seamlessly process information that they receive in a driving environment; that is, human factors such as cognitive load are not factored in the response. More importantly, no study has explicitly addressed the role of information perception in the decision-making process which can possibly lead to challenges such as information overload and information-induced confusion. These perception aspects are fundamental components of the driver's real-world travel environment related to route choice decision-making, and need to be holistically considered along with driver attitude towards information and past travel experience, to enable realism in inferring driver behavior under information provision in the inherently interactive multitasking driving environment. In summary, past literature have primarily focused on the tangible benefits of real-time information (such as travel time savings and reduction in travel time uncertainties) on route choice behavior, and have at large overlooked the importance of human factor aspects and psychological effects in drivers' route choice decision-making process. This study proposes the concept of an information-related psychological process to explicitly illustrate the role of information perception from a psychological standpoint and its implications for route choice decision-making.

Recent advances in in-vehicle driver monitoring systems have enabled non-intrusive real-time tracking of several physiological factors (such as eye blinking and gazing behavior, heart rate, facial expressions, etc.) that can be used to infer driver cognitive state, which includes cognitive workload, distraction, and level of engagement, using psychophysiological analysis. Past studies have developed methods to estimate drivers' distraction and cognitive workload associated with information systems using eye activity behavior such eye fixation (that is, maintaining the visual gaze on a single location), saccade rate (that is, fast eye movement that occurs when the visual attention shifts from one location to another), and blink rate (that is, semi-automatic rapid closing of the eyelid) to infer driver cognitive state such as cognitive workload, level of fatigue or drowsiness, and level of attention and situational awareness (Benedetto et al., 2011; Faure, Lobjois, & Benguigui, 2016; Heikoop, de Winter, van Arem, & Stanton, 2017; Liao, Zhang, Zhu, & Ji, 2005; Palinko, Kun, Shyrokov, & Heeman, 2010; Ranney et al., 2013). Several studies have developed models based on facial expressions (for example, yawning behavior, head movements and eye blinking behavior) to estimate driver's fatigue level (Ji, Zhu, & Lan, 2004; Liao et al., 2005). In addition, several models have been proposed in the literature to use facial expressions for estimating human emotional state (Bassili, 1979; Busso et al., 2004). Several experimental studies have used data from electroencephalogram (EEG) and electrocardiogram (ECG) to determine driver's cognitive workload, driver distraction, fatigue level and stress level in driving context, and their effects on driving performance (Bos, 2006; Brown, Johnson, & Milavetz, 2013; Haak, Bos, Panic, & Rothkrantz, 2009; Lin, Wu, Jung, Liang, & Huang, 2005). From neurocognitive science, empirical models have been developed to estimate cognitive workload, drowsiness and engagement level for general activities using experimental data (Berka et al., 2005, 2007). Some studies used secondary task analysis and self-reported survey-based methods to determine driving performance under the provision of real-time information while driving (Faure et al., 2016; Harbluk et al., 2013; Ranney et al., 2013). In summary, past literature has focused on developing psychophysiological models using variety of biosensors (both in isolation and in combination) to estimate several aspects of driver's cognition, but most of the studies focused primarily on driving performance from safety implications perspective. In this context, this study develops a psychophysiological model to capture the cognitive effects induced by real-time information using physiological indicators and their impacts on driver route choice behavior.

Driving simulators are used to study driver behavior in a safe and controlled environment. Past literature have used driving simulators to study fatigued, drowsy and inattentive driving (Charlton and Starkey, 2013, 2011; Dong et al., 2011; Rimini-Doering et al., 2001), impacts of interactions with IVIS on driver cognitive workload and distraction (Benedetto et al., 2011; Birrell & Young, 2011), working memory and cognitive load using secondary task methods (Heikoop et al., 2017; Nijboer et al., 2016; Ross et al., 2014), route choice behavior (Ben-Elia et al., 2008), role of assistive technologies for people with diverse abilities (Lancioni & Singh, 2014), automobile collisions (Mcmanus, Cox, Vance, & Stavrinos, 2015), and for driving and non-driving task learning purposes (Pam Goheen, 2011; Ritterfeld, 2005). This study conducts interactive driving simulator experiments to collect a variety of data (for example, driving performance, self-reported surveys, physiological indicators, etc.) to analyze driver route choice behavior under real-time information provision from the perspective of driver cognition. This study develops a hybrid route choice model incorporating psychological effects (which include cognitive burden, cognitive decisiveness and emotional relief) induced by real-time travel information as latent variables, which uses indicator variables based on a self-reported survey. The effects of the situational factors (such as trip purpose and traffic congestion), real-time travel information characteristics (such as amount, content and source), and individual driver characteristics (such as age, gender and education) are also incorporated in the model. Then, this study performs psychophysiological analysis to estimate driver cognitive state in a tangible manner using driver physiological indicators under real-time information, and analyze its impact on driver route choice behavior.

1.2 *Organization of the report*

The remainder of the report is organized as follows. CHAPTER 2 discusses the design of driving simulator experiments. CHAPTER 3 presents a hybrid route choice model incorporating the psychological effects of real-time information on route choice decision-making process. CHAPTER 4 discusses the impacts on driver cognition, estimated using measured physiological indicators, under real-time information. CHAPTER 5 summarizes the research findings and insights, and discusses future research directions.

CHAPTER 2. DRIVING SIMULATOR EXPERIMENTS

2.1 *Purdue University driving simulator laboratory*

The driving simulator laboratory at Nextrans Center, Purdue University (illustrated in Figure 1) is a state-of-the-art experiment facility to capture human factors under dynamic transportation environments (Nextrans Center, 2015). The driving simulator consists of key driving components such as dashboard, steering wheel, ergonomic driving cockpit, three wide screens, etc. (OKTAL, 2017). This study includes two interactive driving simulator-based experiments (with and without integrated biosensors capturing participating drivers' physiological data) to analyze the cognitive effects induced by real-time travel information provision while driving, and its impacts on the route choice decision-making process.

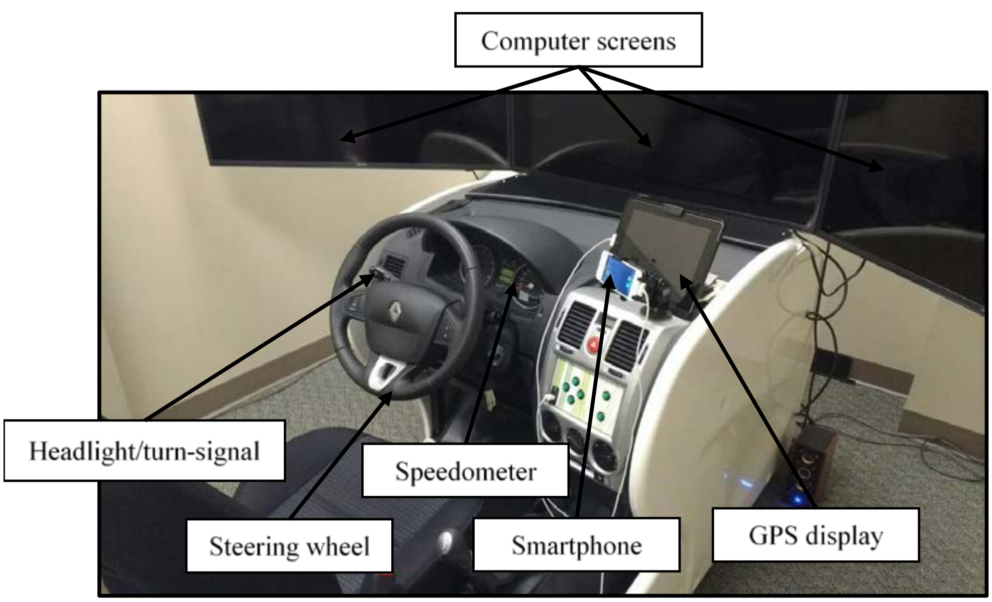

Figure 1. Interactive driving simulator at Nextrans Center, Purdue University

A realistic road network of northern Indianapolis, IN (as shown in Figure 2), is constructed as a terrain of the driving simulator-based experiments. The experiment scenarios are designed to capture the effects of traffic conditions (such as congestion level and accidents) and real-time information characteristics (such as amount, content, source and sensory modality). While traveling from a fixed origin to destination, participating drivers can choose/change their route between two options (freeway and arterial options) at three decision-making points (Figure 2). While a route choice decision at the first decision-making point (A) is depending on driver's initial preference and prior experience (if any), the other two route choice decisions (at B and C) are also influenced by real-time travel information provided. To ensure realistic driving environment, the driving simulator is integrated with a microscopic traffic simulator to generate dynamic and responsive ambient traffic which is consistent with the experiment scenario provided. Additionally, a point-based compensation reward system is developed to overcome the common criticisms of the driving simulator-based studies, that is, an intent for the participant driver to complete his/her trip within the assigned time limit, and not to treat the simulator as a game and follow the traffic rules as in real-world.

Figure 2. Map of the network for driving simulator experiments

A pre-experiment survey is designed to collect data on participant's individual characteristics such as sociodemographic data (such as age, gender and education), and attitude towards and experience with real-time information systems (such as trust and familiarity). Based on the assigned experiment scenario, the participant drives three to five experimental runs. A stated preference survey is conducted before each experimental run to collect driver's pre-trip route choice preference. During each experimental run, data is collected on driver's route choices, disseminated real-time information characteristics, traffic conditions, and micro-level driving performance (such as steering wheel angle, brake/gas pedal pressure, and lane and headway maintenance). During each experimental run, data related to information perception and cognitive effects related to the provided information are collected using self-reported surveys shortly after making information-aided route choice decisions while pausing the simulation. After the trip is over, a post-run survey is conducted to capture drivers' satisfaction and travel experience.

Driver's physiological data (such as eye movements, brain electrical activity and heart rate) is collected using biosensor devices: (i) B-Alert X24 Wireless Headset system that includes EEG and ECG (Advanced Brain Monitoring, 2017); and (ii) wearable eye-tracking glasses (SensoMotoric Instruments, 2017). The micro-level driving performance and physiological data are used to estimate driver's cognitive state (such as cognitive workload, distraction, and level of engagement) under real-time travel information provision while driving. Such behavioral and physiological data obtained from the experiments can be a valuable source to understand traveler behavior and its underlying psychological factors especially under information-rich driving environments.

2.2 *Experiment Procedure*

The participants were recruited among the staffs and students in Purdue University, and people living in Greater Lafayette area and Indianapolis. A web page link (www.purdue.edu/drivingsimulator) with experiment description was disseminated with advertising emails, flyers, and postcards, allowing interested participants to access more detailed information about the experiments. Participants of experiments with integrated biosensors are asked their history of motion sickness, mental or physical impairment, status of regular medication, and whether they wear corrective glasses to qualify for participation.

The qualified participants schedule a time for participation using an online portal or by contacting the NEXTRANS Center through email or phone. Participants are required to complete a pre-experiment survey, which includes questions on participants' sociodemographic characteristics, attitudes towards and experiences with real-time travel information and travel preferences before they come to the driving simulator laboratory. On completion of the survey, the participants are asked to provide an email address or phone number, which confirms participant's completion of the survey. For experiment with integrated biosensors, the participant needs to take the following preparatory actions before coming to the center: (i) Wash hair and do not use any hair products on the day of experiment; (ii) No medication for at least 8 hours prior to the experiment, (iii) No caffeinated food or beverage should be consumed for at least 8 hours prior to the experiment. Upon arrival, participants provide written consent to participate in experiment. Participants are informed that, in due course of the experiment, if they are not comfortable they can withdraw from participating at any time. The steps of experiments are presented in Figure 3.

The purpose and procedure of the experiment are explained to the participants before starting the experiments. The participants are specifically asked to drive just as they drive in real world rather than representing the expected best driving behavior or treating the simulator driving as a game. This is critical for the experiment as there is a possibility that participants may tend to be artificially more compliant or less responsible in simulation than in their usual driving.

Before participants drive in the simulator, we introduce the characteristics of road network including origin-destination, available routes, and route choice decision-making points. Then, a practice session is conducted with two objectives: (i) to ensure their familiarity with driving in simulator environments; and (ii) to construct a desired level of familiarity for a participant by controlling certain aspects of practice session such as trip route, availability of GPS, etc. In addition, during the practice session, the participants are monitored if they are feeling motion sickness or any other uncomfortableness, which leads to termination of the experiment.

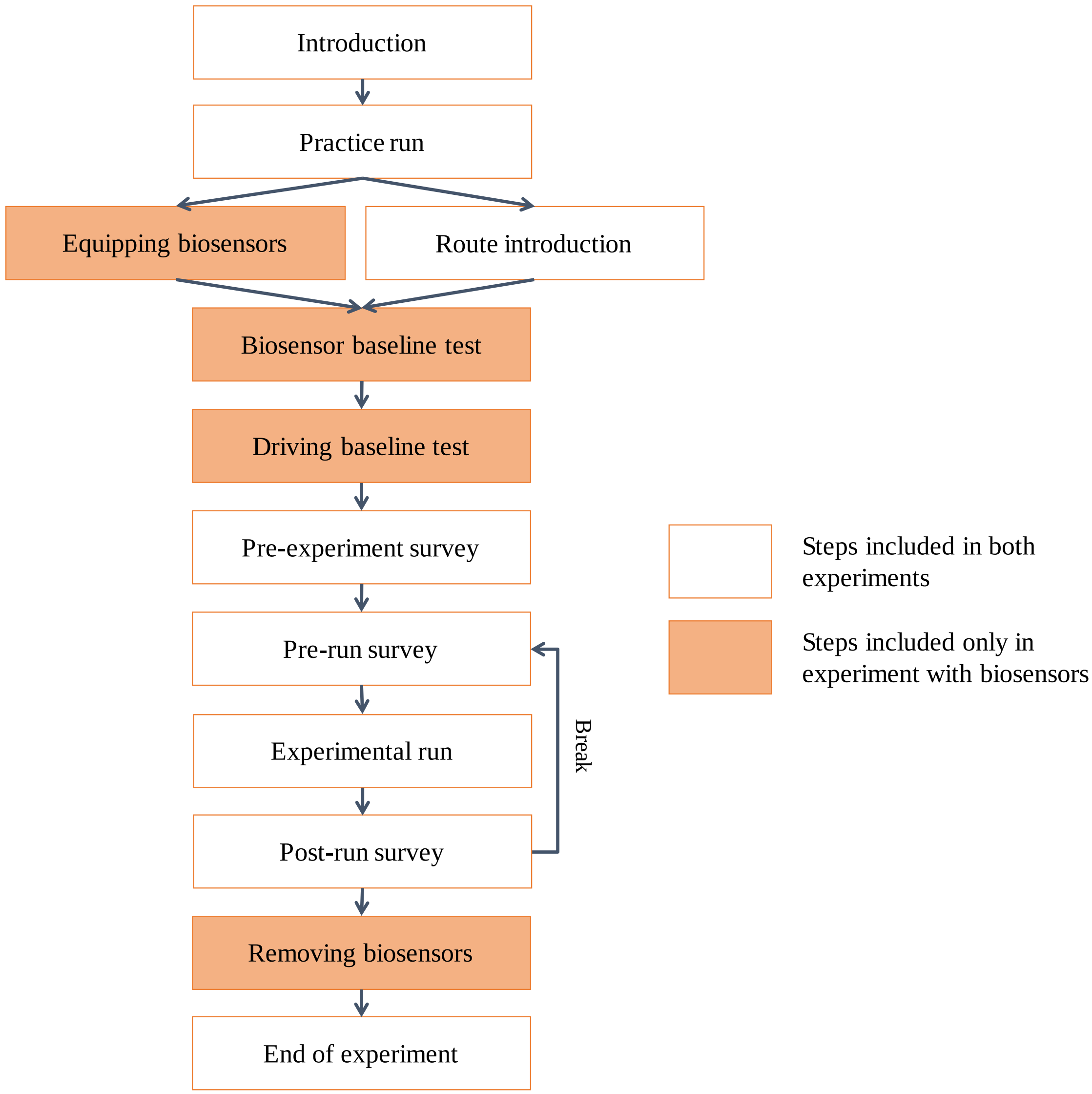

Figure 3. The steps of driving simulator experiments

After practice session, the participants are equipped with biosensor devices, which includes EEG and ECG for the experiments with integrated biosensors. This step requires the application of conducting gel between the skin and EEG/ECG sensors. The sensor impedances are calibrated and validated, and re-adjustment of sensor locations are made if the quality of sensor data is not satisfactory. Then, baseline tests are performed by participants to establish baseline metrics (cognitive workload and engagement) to analyze biosensor data obtained from driving simulator experiments. These tests consists of three tasks: 3-choice psychomotor task (duration is approximately 7 minutes), eyes open (duration is approximately 6 minutes), and eyes closed (duration is approximately 6 minutes). A summary of the performed baseline tests is presented in Table 1. In each task, participants are required to respond as quickly as they can to different kinds of stimuli (visual and auditory). The brain activity during these tasks is used to define low and high state of participants' alertness or engagement. In addition, baseline tests are designed to assess individual brain activity (cognitive workload) while performing easy problem-solving tasks. Next, participants are equipped with eye-tracker device and it is calibrated to achieve satisfactory data quality. Then, participants are asked to perform a driving baseline test to establish brain response to simple driving tasks. The road network they drive in the driving baseline test is the same network that they will drive during experimental runs but without traffic. In this test, participants should follow simple driving instructions presented on a screen (such as "Maintain Speed Limit" or "Turn Left onto Meridian Street").

The participants need to complete five experimental driving runs in experiment without biosensors and three experimental driving runs in the experiment with integrated biosensors. Before and after each experimental run, the participants are asked to fill out a short survey related to their route preferences (Pre-run surveys) and their satisfaction and travel experience (Post-run surveys). In each run, different real-time travel information are provided to participants based on the assigned information scenarios. For the driving simulator experiments without integrated biosensors, another set of questions regarding information perception (Within-run surveys) are asked shortly after making information-aided route choice decisions during the experimental runs. Participants are required to take a five-minute break between two consecutive experimental driving runs. In the experiments with integrated biosensors, wearable eye-tracker device is removed after each run to allow the participant to move freely during the break. Before the beginning of a new run, the eye-tracker device should be re-applied and calibrated.

Table 1. Summary of baseline tests

Name of task	Duration (minutes)	Activity	Purpose
B-Alert baseline test			
3-choice psychomotor task	7	Recognize shapes demonstrated on the screen and react accordingly	Capture brain activity while performing basic problem-solving activity
Eyes open task	6	React to visual stimuli as soon as possible by pressing a key	Capture brain reaction to visual stimuli
Eyes closed task	6	React to auditory stimuli as soon as possible by pressing a key	Capture brain reaction to auditory stimuli
Driving baseline test			
Driving task	15	Driving in experimental network without traffic, while following simple instructions (e.g. maintain speed limit, turn left, etc.)	Capture brain activity while performing basic driving tasks

After the experiments, participants are compensated by cash in both experiments, ranging from $10 to $60. The total compensation is calculated by a developed point-based reward system factoring the number of runs completed and realistic driving performance. The total compensation is also reduced for treating the simulation as a game and for excessive speeding and/or traffic violations.

CHAPTER 3. ROLE OF PSYCHOLOGICAL EFFECTS OF REAL-TIME TRAVEL INFORMATION IN ROUTE CHOICE DECISION-MAKING

3.1 Objective

This study seeks to investigate the psychological effects of real-time travel information on traveler route choice behavior. A behavior model incorporating the psychological states of travelers in relation to information, is proposed to explicitly account for the latent psychological effects on the decision-making process. A systematic experiment design framework using an interactive driving simulator integrated with a real-time microscopic traffic simulator, is used to conduct experiments to obtain data on routing behavior and information perception indicators.

3.2 Conceptual framework for psychological effects of real-time travel information

In this study, four facets of information perception – ease of comprehension, sufficiency, consistency, and favorableness – are specified to characterize the psychological effects of information provision. Ease of comprehension implies information perception in terms of cognitive complexity (how clearly the information is presented) and cognitive load (amount of information) of the provided information. Sufficiency implies information perception in terms of whether the provided information satisfies traveler’s information needs for informed decision-making. Consistency represents information perception in terms of the consistency between: (i) the provided information and past travel experience, or (ii) information from multiple sources. Favorableness refers to information perception in terms of whether the provided information is favorable to the traveler’s trip context (for example, based on the trip purpose or destination); that is, travel conditions implied in the provided information are desirable for the specific trip being made. Based on the information perception and other explanatory factors (such as traveler attributes and situational factors), three psychological effects of real-time travel information – cognitive burden, cognitive decisiveness, and emotional relief – are assumed to affect route choice decision-making. *Cognitive burden* refers to the amount of mental effort that needs to be expended in processing information-related cues in the driving environment. *Cognitive decisiveness* refers to the level of awareness in comprehending the travel situation, and the level of uncertainty reduction in making decisions, based on the provided information. *Emotional relief* refers to the level of mental relief due to the anticipation of future outcomes, based on the provided information.

Figure 4 illustrates the roles of the latent psychological effects (dashed lines and arrows) in the conventional structure of route choice decision-making process under information provision. These latent psychological constructs will be identified through observed indicators collected by driving simulator experiments.

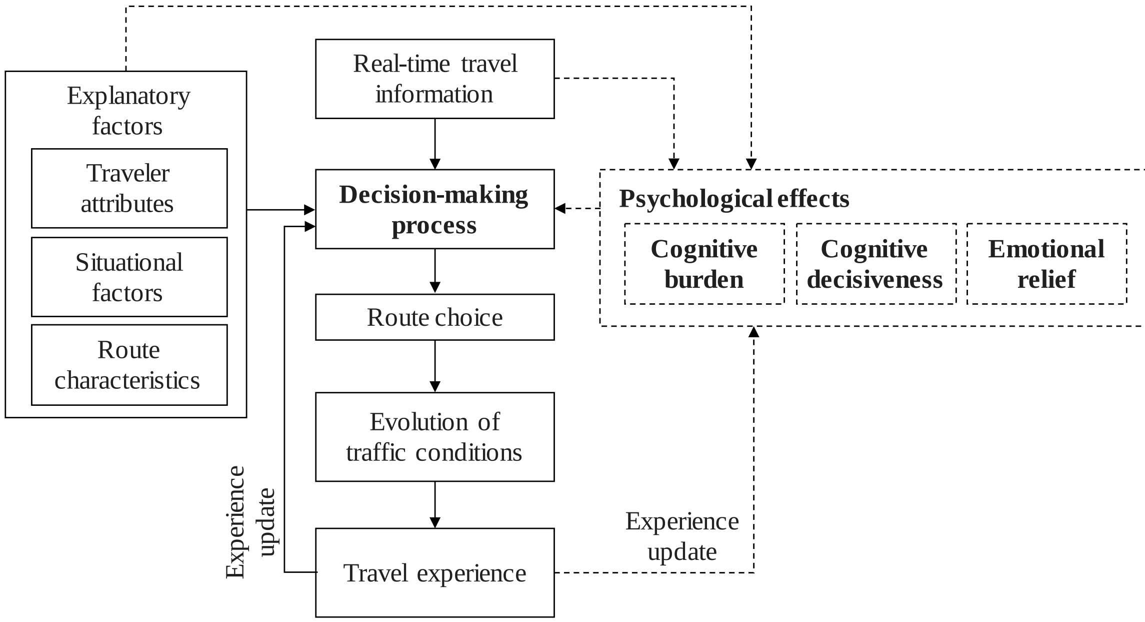

Figure 4. Route choice decision-making process under real-time travel information provision

3.3 *Modeling approach*

To address the impacts of various contributing factors including not only observable explanatory factors but also unobservable psychological effects of information on traveler route choice, a latent variable-based approach is required. This study adopted a framework of hybrid choice modeling associated with latent variable modeling structure to illustrate the role of the both observable and unobservable factors in route choice decision-making process.

Figure 5 depicts the proposed framework that is comprised of two sub-components: (i) a latent variable model to capture travelers' psychological effects based on the associated indicators and the observable explanatory variables, and (ii) a random utility discrete route choice model with latent variables to account for the decision-making process factoring the psychological effects of information as well as other traditional explanatory variables. By including the latent variables in the discrete choice model, it is able to investigate the roles of psychological effects of real-time travel information in route choice behavior.

A hybrid choice modeling framework (Walker & Ben-Akiva, 2002) based on the multiple indicators multiple causes (MIMIC) structure (Bollen, 2002) is adopted to investigate route choice decision-making with the consideration of psychological effects of information provision. The proposed framework consists of components: (i) a latent variable model and (ii) a hybrid choice model for route choice decision-making. In the latent variable model, the psychological constructs are inferred based on information perception indicator variables (Equation 1), while the impacts of other explanatory variables (such as traveler attributes, situational factors, route characteristics and information characteristics) on the psychological constructs are considered (Equation 2). On the other hand, the utility function of the proposed hybrid route choice model includes both the latent variables for psychological effects and observed explanatory variables (Equations 3 and 4). Here, the revealed route choice behavior, the dependent variable, has a binary choice: staying on the current route or switching to the alternative one.

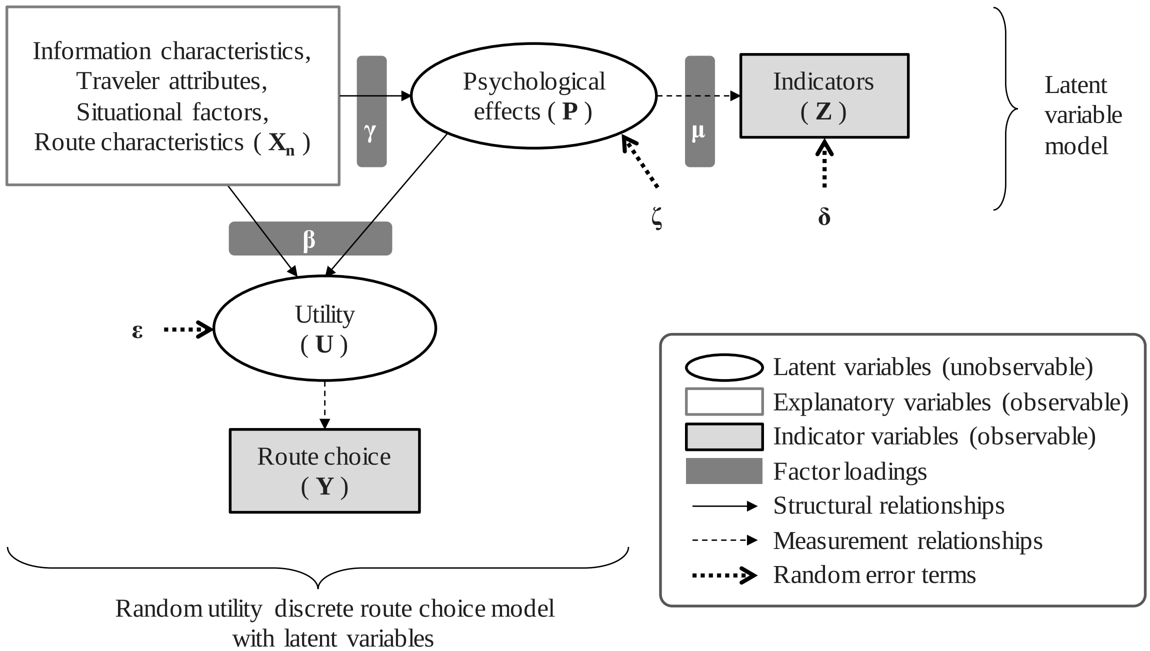

Figure 5. Conceptual framework of hybrid route choice modeling

$$Z_n = \mu^Z P_n + \delta_n^Z \qquad \delta_n^Z \sim N\left(0, \Sigma_{\delta_n^Z}\right) \tag{1}$$

$$P_n = \gamma^P X_n + \zeta_n^P \qquad \zeta_n^P \sim N\left(0, \Sigma_{\zeta_n^P}\right) \tag{2}$$

$$U_{in} = \beta_X X_n + \beta_P P_n + \varepsilon_{in} \qquad \varepsilon_{in} \sim Gumbel\left(0, \Sigma_{\varepsilon_{in}}\right) \tag{3}$$

$$Y_{in} = \begin{cases} 1 & if\ U_{in} = \max_j\{U_{jn}\} \\ 0 & otherwise \end{cases} \tag{4}$$

Z_n is a vector of indicator variables for individual *n*, P_n is a vector of latent variables for individual *n*, and μ^Z is a matrix of coefficients indicating factor loadings. γ^P is the coefficient vector for the other (observed) explanatory variables X_n which include traveler attributes, situational factors, route characteristics and information characteristics. The measurement error δ_n^Z and the structural error ζ_n^P are assumed to be independently and identically multivariate normally distributed. U_{in} is the random utility of alternative *i* for individual traveler *n*, P_n is a vector of latent variables for traveler *n* identified in the latent variable model, and β_P is the coefficient vector of P_n. β_X is the coefficient vector for the other explanatory variables X_n. The disturbance term ε_{in} is independently and identically Gumbel distributed.

3.4 Results and discussion

Participants who are at least 18 years old and holding a valid driver's license were recruited from Purdue University and local communities in Lafayette and West Lafayette, Indiana. A total of 206 participants successfully completed the prerequisite online survey and the following on-site driving sessions. Since each participant executes 3 to 5 runs with diverse travel and information scenarios, a total of 722 observations of route choice decision-making under information provision are obtained from the experiments.

The key findings related to information characteristics and psychological constructs are as follows. While a higher amount of information expectedly increases *cognitive burden*, it helps travelers to have an improved *cognitive decisiveness* regarding the traffic situation. *Cognitive decisiveness* is also enhanced by alternative route information provision. By contrast, *emotional relief* is particularly influenced by the GPS navigation information for the alternative route rather than real-time travel information.

The role of the psychological effects of information provision on the route choice decision-making is shown to be statistically significant. *Cognitive burden* implies that if all other conditions remain equal, travelers with higher cognitive load are more likely to stay on the current route. This implies that the stress from information overload or information-induced confusion can weaken the influence or effectiveness of information to alter travelers' route choice. By contrast, *cognitive decisiveness* has a positive impact on changing route, which means that the reduced uncertainty encourages route changing decisions. That is, if travelers have more clarity on the ambient traffic conditions on the alternative route (higher cognitive decisiveness), they are more likely to choose it when it has better traffic conditions. *Emotional relief* also has a positive influence on switching route to the alternative one. That is, if a traveler feels the information is favorable (for example, available option of alternative route with a shorter expected travel time), he/she would change to the route.

Incorporating the psychological effects of real-time travel information provision can improve the understanding of travelers' route choice decision-making behavior. Comprehensive experiments are designed using an interactive driving simulator integrated in real-time with a microscopic traffic simulator. The estimation results illustrate that the proposed hybrid route choice model, through its consideration of psychological effects, can better explain the traveler route decision-making behavior under information provision. The roles of information perception in multiple dimensions and the psychological effects of information are identified and verified. The study results can provide system operators with insights for developing effective strategies for information creation and provision based on the holistic understanding of route choice behavior to improve system performance (such as reducing congestion).

CHAPTER 4. PSYCHOLOGICAL IMPACTS OF INFORMATION ON ROUTE CHOICE BEHAVIOR

Results in previous chapter show that cognitive and psychological effects induced by real-time travel information play important roles in driver's route choice decision-making process, which can have implications for transportation network operation and travel information management. A key limitation of presented model is that the psychological effects are considered as latent variables that are indirectly estimated using self-reported surveys conducted in the middle of the experimental runs, which can intervene with participant's psychological state and yield several biases (Spector, 1994). In this context, the experiments has been modified to use integrated biosensors and collects physiological data in a non-intrusive and direct manner to infer on driver cognitive state.

Very few studies have considered the impacts of real-time travel information that goes beyond the physical benefits to the drivers such as travel time savings. Reassured feeling or uncertainty reduction in estimated travel time by factoring the cognitive effects of information has not considered as impacts of real-time travel information provision. However, these modeling frameworks are often limited in their ability to capture the cognitive effects in a quatifiable manner due to their data collection methods. For example, previous chapter presents a developed hybrid route choice model that incorporats psychological effects (which include cognitive burden, cognitive decisiveness and emotional relief) induced by real-time travel information as latent variables, which uses indicator variables based on a self-reported survey. Some studies have developed methods to estimate drivers' distraction and cognitive workload associated with information systems using physiological factors such as eye blink behavior, heart rate, brain electrical activity, etc. (Berka et al., 2005; Brookhuis, Vries, & Waard, 1991; Brookhuis & de Waard, 2010; Dong et al., 2011; Faure et al., 2016; Haak et al., 2009; Ji et al., 2004), but their focus is limited to driving performance assessment or safety implications.

In this context, this study aim to evaluate the efficacy of the biosensors in monitoring cognitive workload during complex cognitive tasks such as driving under real-time information provision, and identify the cognitive workload induced by information-related stresses by separating workload due to stresses from driving and non-driving activities.

Several studies (Berka et al., 2007; Harris, Schroer, Anderson, & Moeller, 2012; Johnson et al., 2011) concluded that EEG had the potential to be an objective measure of cognitive workload. Those studies reported the shift in EEG signals in response to changes in task complexity. Driving is a complex task that is highly engaging and requires significant amount of allocated recourses that can vary based on driving environments, trip purpose, secondary tasks, etc. Hence, if cognitive workload induced by real-time information is measuring during driving the multiple stresses can cause shift in EEG signals. It is possible, that perceptual processes or motor activity due to driving task can be captured by shift in EEG signals and not cognitive workload due to information stresses. In our study, we design driving simulator experiments that measures driver's cognitive workload with real-time travel information provision by integration of EEG and eye-tracker data.

For this purpose, physiological sensor data (from driving simulator experiments) are employed to analyze the cognitive effects induced by real-time travel information provision while driving, and their impacts on the route choice decision-making process. Then, causal relationships between cognitive states under real-time travel information provision, micro-level driving performance and driver route choice behavior are illustrated based on the collected physiological data.

4.1 Methodology

We develop a framework to describe causal relationships between cognitive effects under real-time travel information provision, and micro-level driving performance and driver route choice behavior. To do that, biosensors for physiological data collection are integrated with interactive driving simulator environments. Driver response to information in terms of impacts on driving performance and driver cognitive state under real-time travel information provision is analyzed. Before the experiment begins, baseline metrics are defined indicating brain response to basic driving tasks. During three experimental runs with different traffic and information scenarios, the following data is collected: (i) microscopic driving performance (such as steering wheel angle, brake/gas pedal pressure, and, lane and headway maintenance); (ii) experiment scenario details and real-time information characteristics; (iii) participant's self-reported data related to information perception and driver cognitive state collected using survey after each experimental run; (iv) cognitive metrics based on brain activity (which include cognitive workload and level of engagement) using EEG; (v) heart rate using ECG; and (vi) eye movement data (such as gaze pattern, blink rate, fixation and saccades) from eye-tracker device.

Physiological factors observed using EEG and eye-tracker devices are used simultaneously to determine driver cognitive states and identify reason of changes in cognitive states under real-time information provision. For example, the level of engagement recorded by EEG does not determine the cause of engagement. To overcome this limitation, we develop methods for integrating eye movement-related metrics collected by the eye-tracking device with EEG data to corroborate the level of engagement due to driving activity, non-driving activity and/or visual information. In addition, we use the survey data collected before and after each experimental run to verify the information perception and cognitive states of drivers estimated using EEG and eye-tracker data.

4.1.1 Psychophysiological data

Drivers' cognitive states are estimated by using psychophysiological signalsincluding brain activity, heart activity, and eyeball movements. Brain activity is represented by brainwaves which are initiated in brain cells (neurons) by electric signals in response to different stimuli. The brainwaves are differentiated by its location in the brain in which they are initiated (or channel), amplitude and frequency. In this study, brain activity characterized by two aspects: cognitive workload and engagement. Both cognitive workload and engagement are related to the amount of mental recourses being used. While cognitive workload reflects cognitive processes such as problem solving, integration of information, and/or analytical reasoning, engagement is involvement in information-gathering, visual processing, and/or allocation of attention. Hence, drivers' cognitive workload can be used to diagnose driver fatigue, drowsiness and/or stress. On the other hand, engagement can be used as a metric of vigilance and situation awareness while driving. Since both cognitive workload and engagement reflect important aspects of driving performance, they are required to be monitored and analyzed simultaneously to avoid estimation errors in driver's cognitive states under real-time travel information provision.

The EEG and the functional magnetic resonance imaging (fMRI) are two non-invasive tools commonly used to measure brain activities. Although, using EEG to measure brain activity is usually time-consuming, EEG is chosen to measure brain activity for its flexibility and afforability. There are well-established approaches used to quantify brain activity including (i) *computation of the power spectral densities*, allowing to describe cognitive states that are at a high level (intencive problem-solving brain activy, sleeping, drowsing). (ii) *ratios between different frequency bands*, describing cognitive functions at a more detailed level (differentiate level of mental computational efforts, etc.), and (iii) *N100 and P300 components of the event-related potential*, capturing impacts of short events on brain activity. These approaches consider a limited number of (one or two) wide brainwave bands to define different cognitive states. However, this can lead to either misclassifications or oversimplifications of the cognitive processes. In addition, in previous attempts to measure cognitive workload, it was found, that the changes in brainwave signals follow different patterns based on the type of performed tasks. Particularly, significant differences were found between the tasks that require more visual sensory processing and the tasks that require more memory resources. To address the issues, this study adopts models developed by Advanced Brain Monitoring, Inc. in analyses of the collected EEG sensory data. The models have been tested by a series of studies in different experimental environments including vigilance tests (Berka et al., 2005; Johnson et al., 2011), problem solving tests (Berka et al., 2007), memory tests (Berka et al., 2007), and driving tests (Lei & Roetting, 2011; Wang, Chen, & Lin, 2014).

In the models, cognitive workload is characterized by 30 variables representing electric signals from six channels at different frequencies. Since cognitive workload measures the cognitive processes associated with problem solving and decision-making, increment in level of difficulty of mental arithmetic or other problem-solving tasks results in increased cognitive workload. In contrast, engagement is depicted by 23 variables representing electric signals from two channels, and is related to processes involving information-gathering, visual scanning, and sustained attention. Hence, engagement level is correlated with complexity level of stimulus processing, and amount of allocated attentional resources. Engagement does not increase with neither increased difficulty of mental arithmetic nor increased complexity of analytical reasoning. Combination of cognitive worload and engagement can illustrate most of cognitive tasks performed by human.

Another psychophysiological measure that can reflect drivers' cognitive state is a heart activity, in particular, heart rate and heart rate variability. The ECG sensors are used to monitor the heart activity. It is easily measured through a few electrodes attached to the human body and can be analyzed in real-time. The heart rate is defined as a number of heart beats within a fixed period of time. The heart rate variability is defined by variability in duration and oscillation patterns of heat beats. Both heart rate and heart rate variability were found to be correlated with cognitive workload, where heart rate is increasing and heart rate variability is decreasing with increase in workload.

Although EEG and ECG are widely used for medical purposes, their use in detecting cognitive workload in other research domains is not very common for two reasons: (i) difficulty in applying sensors in a "field" studies and (ii) difficulty in analyzing the collected data. To address the first difficulty and increases the flexibility in usage of EEG and ECG devices, a wire-less headset is used in the study (Figure 6). Biosensor data is transmitted using bluetooth connection and stored in a designated computer, and can be analyzed in real-time as well as offline. Integrated software solutions associated with EEG and ECG devices are used to analyze the collected data. Users can access to raw data from each sensor in a graphical or spreadsheet format. In addition, this software package provides preliminary data processing functions including removing artifacts (e.g., effects from eye blinks, electrical interference by outside sources, electrical noise from elsewhere in the body, poor contact, etc.), and data split in brainwave bands for each sensor.

(i) ¶ (ii) (iii)

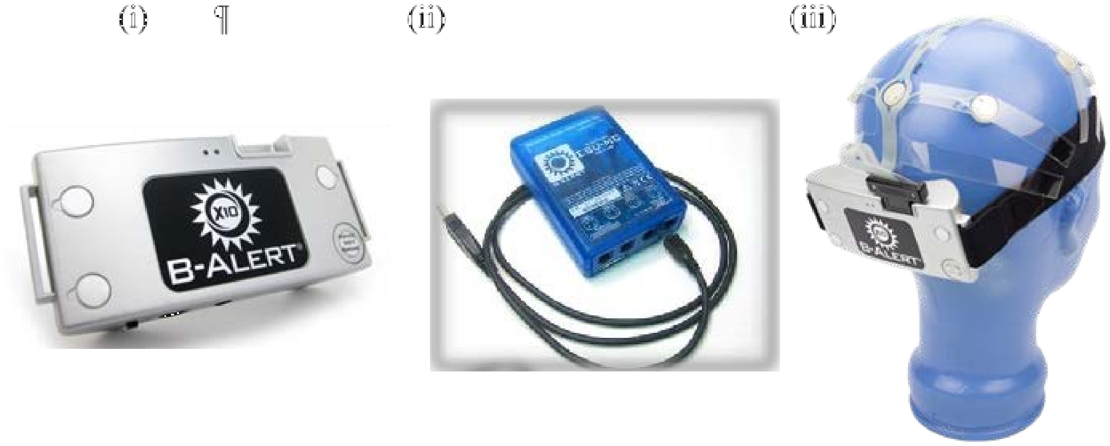

Figure 6. EEG device set; (i) headset, (ii) receiver, (iii) headset equipped

4.1.2 Eye-tracker video data processing

In this section, a framework used to detect objects in eye-tracker videos and process the video data is discussed. The objective of this framework is to determine AOI in eye-tracker video recordings to enable identification and quantification of eyeball activities while driving. The processing methods are based on image processing techniques. The eye-tracker video is divided into several frames, then each frame can be transformed into binary image through different methods. The binary image can be treated as a matrix with 0 and 1, where 0 and 1 represents the black and white parts in the binary image, respectively. Further manipulations with binary images allow to identify the areas of interests (AOI). By combining the results of AOI identification and coordinates of eye gaze points, the duration of fixation on specific AOI (if any) can be calculated. This allows to understand the source of changes in driver cognitive state (due to driving of non-driving activity or due to information provided) by identifying the objects participant is looking at.

There are two categories of AOI that needed to be detect (Figure 7). First AOI category includes continuous objects (AOI that maintain location and size through the eye-tracker video), such as the TV frame, clock on the screen, rearview mirror and dashboard panel. Second AOI category includes discontinuous objects (AOI with varying location and size through the eye-tracker video), such as road signs and signals. Figure 7 illustrate examples of two categories of AOIs.

(i) Continuous AOI

(ii) Discontinuous AOI

Figure 7. Examples of (i) continuous and (ii) discontinuous AOIs

Figure 8 summarizes the procedure used to analyze eye-tracker video. First, an eye-tracker video is divided into frames. Then, the background subtraction is performed for each frame of the eye-tracker video followed by AOIs detection step. TV frame is first AOI that is detected for the following reasons: (i) it is easy to identify and available on all video frames, (ii) other continuous AOIs can be defined within the range of TV frame. Discontinuous AOIs, such as road signs, require more steps to be identified, but are also using TV frame detection as a reference.

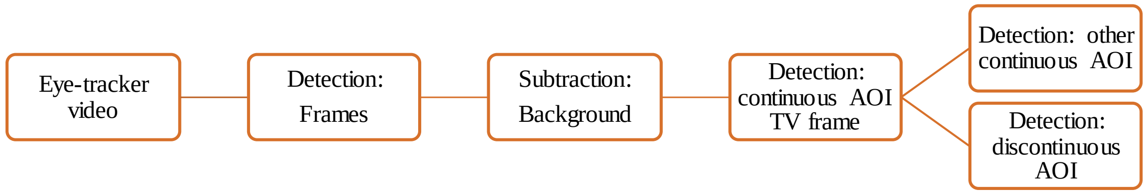

Figure 8. Procedure of eye-tracker video analysis

4.1.2.1 Background Subtraction

Figure 9 shows the flowchart of background subtraction procedure used in this study. For each video frame, first its brightest binary image and blue channel binary image are extracted. Then threshold analysis is conducted on each binary image (threshold values optimal for our settings are identified from several trials). Next, small objects of each binary image are removed. Then, two binary images combined in one image. Result of background subtraction procedure is presented in Figure 10. Results show that this approach allows robust identification of middle TV frame.

4.1.2.2 Continuous AOIs detection

To detect continuous AOIs, the first step is to calculate the TV length and width. This step is needed, as a scale of simulator screens varies from person to person because of variation in head location during driving. For each video, we calculate TV length and width once, and they can be used for analysis of all video frames. Figure 11 shows the steps of this procedure. Then, edge detection is performed on the first frame of the video by using the results from background subtraction procedure. Results of edge detection is presented in Figure 12. After detecting the edge of the binary image, lines of the edges and vertex coordinates of each line can be obtained. Those coordinates can be used to calculate size of TV frame. Figure 13 shows the steps of procedure of continuous AOIs detection.

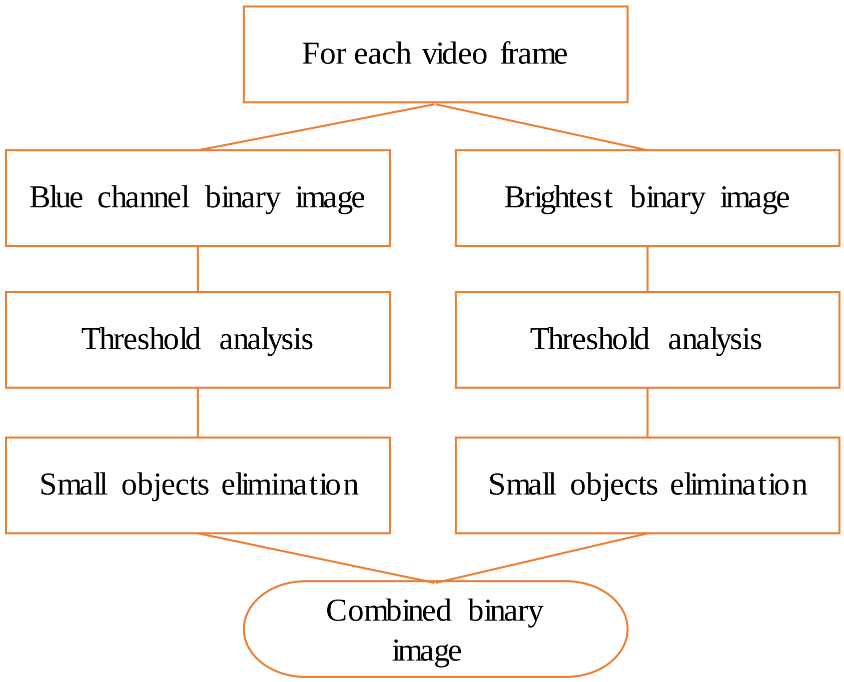

Figure 9. Background subtraction procedure

Figure 10. Results of background subtraction procedure

Then, using background subtraction outcomes, vertex coordinates, and size of the TV frame, the location of right top corners of TV frame of the middle screen (as it always presented in videos) is detected, and it is used as a pivot point to locate other continuous AOI (this is possible as relative locations and sizes of all continuous AOI are stay the same across runs and participants).

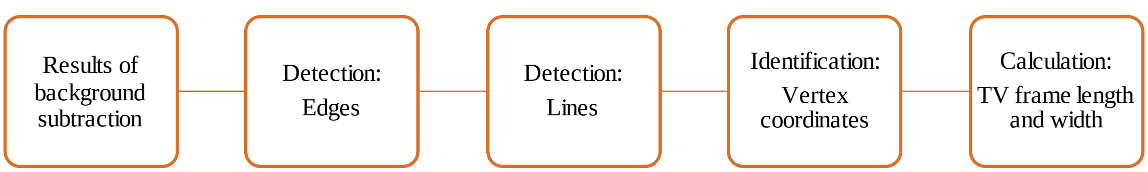

Figure 11. Steps for calculating TV length and width

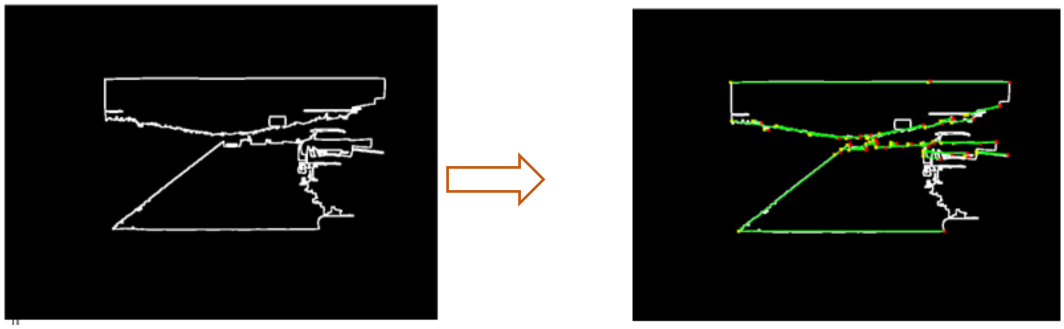

Figure 12. Results of edge and line detections

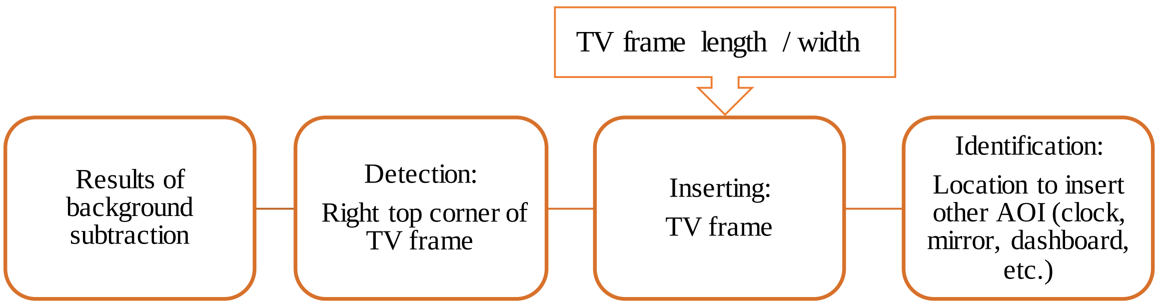

Figure 13. Continuous AOI identification procedure

4.1.2.3 Discontinuous AOI detection

To detect discontinuous AOIs that appear discontinuously through the eye-tracker video (such as road signs), different approaches and procedures than continuous AOIs detection are required. Relative sizes and colors (as they stay the same through the video) of discontinuous AOI are used to perform threshold analysis in object identification procedure. Figure 14 presents the procedure of discontinuous AOI detection. Depending on the color of AOI, different binary images can be used. For example, red channel binary image obtained from each frame can be used to identify green road signs and VMS road signs. The size of TV frame is used as boundaries that identify available area where discontinuous AOIs can be located (they only can be on TV screens). Thresholds analysis and small objects elimination are conducted on the binary image cropped

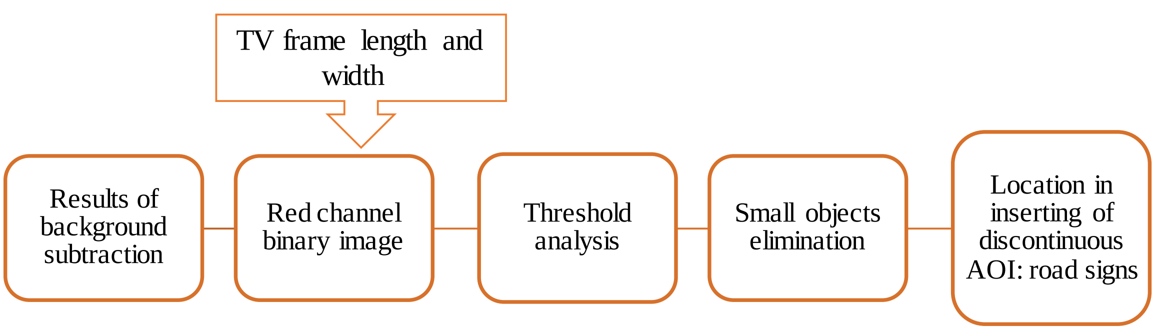

Figure 14. Discontinuous AOI detection procedure

within TV frames. Figure 15 illustrates the result after the objects elimination step. The last step includes mapping the coordinates of identified AOI and inserting them in the original video frames. Figure 16 illustrates the result of the discontinuous AOI detection procedure.

Figure 15. Results of discontinuous AOI identification after the small object elimination step

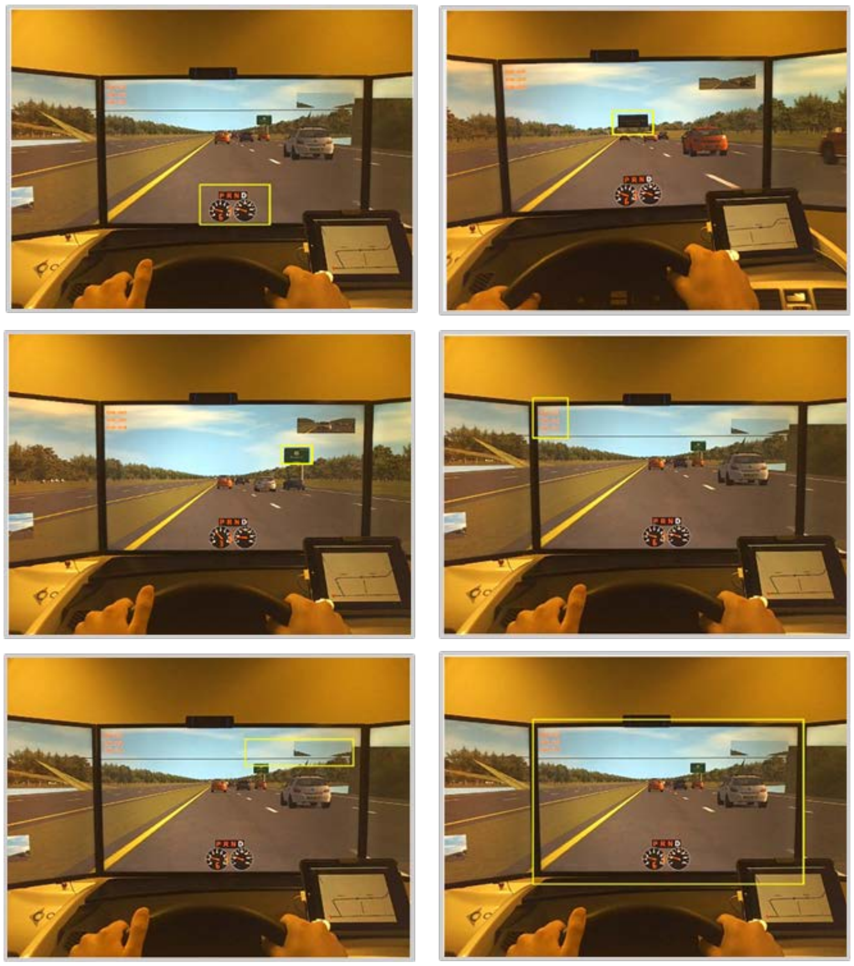

Figure 16. Results of AOI detection framework

4.1.3 EEG data processing

A total of 110 participants (53 females, average age of 26.8 years) are successfully participated in the experiments. All participants are free of neurological and psychological disorders, and self-reported no caffeine at least 8 hours before the experiments. EEG and ECG signals were recorded with 20 and 2 channels, respectively. Before acquiring EEG data, the contact impedances between the EEG electrodes and the skin are calibrated by injecting a conductive gel.

To analyze data, integrated solutions provided by Advanced Brain Monitoring, Inc. is used. Preliminary data processing performed by used integrated solutions including removing artifacts (e.g., effects from eye blinks, electrical interference by outside sources, electrical noise from elsewhere in the body, poor contact, etc.), and data split in brainwave bands.

As driving is a complex task by nature, and it requires significant cognitive resources to perform, there is a need to separate impact of information on driver cognition from impacts of driving and non-driving activities when analyzing EEG data. To capture impacts of voice information, the baseline cognitive state is defined as a brain activity that occurred within 1 second and 1 second before the beginning of the voice information. To capture impacts of VMS on driver cognitive states, the baseline state is defined as a brain activity that occurred within 1 second and 1 second before each time when the participant looks at the VMS (i.e., eye fixation on VMS is detected from eye-tracker video using data for participant eyes gazing activity and coordinates of discontinuous AOI, VMS road sign, using framework discussed above). The baseline cognitive state is defined to capture cognitive state that is consistent with driving conditions before information provision. The average values of cognitive workload and engagement over 1 second interval, measured 1 second before the beginning of the event, are used to characterize baseline driver cognitive state. Then the baseline cognitive values are compared with an average values of cognitive workload and engagement during 1st, 2nd, and 3rd seconds after beginning of voice information and during fixation on VMS (1 second). A complete experiment consists of four driving sessions: one baseline test run with no traffic and without time pressure, and three experimental runs reproducing realistic driving conditions. Baseline test runs are conducted under the same conditions across all participants. However, each experimental run is characterized by information scenarios (in total 8 scenarios). Due to the complexity of driving task, different driving conditions can be presented at the moment of information delivery. In other words, the cognitive state for the periods before and during information provision were not the same across participants in the experimental runs.

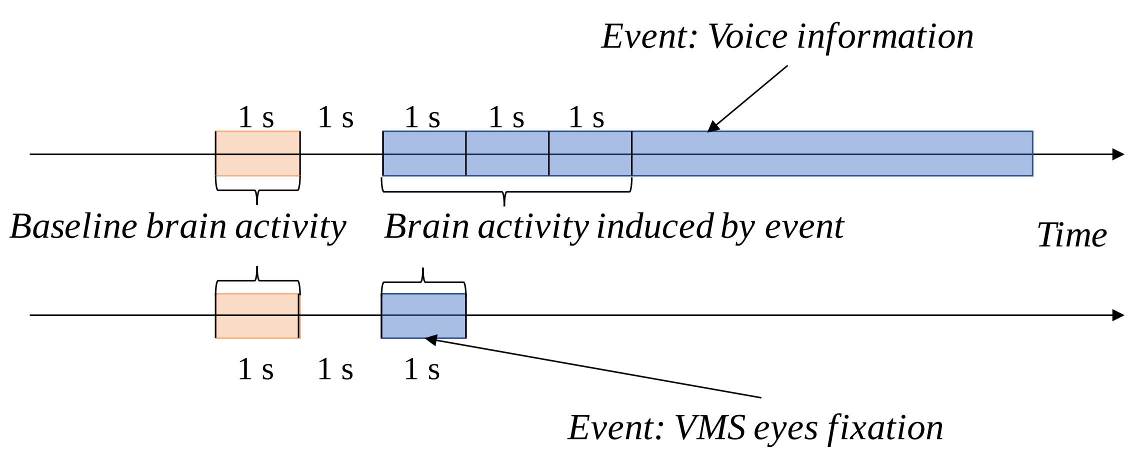

Figure 17. Illustration of time intervals used to identify impacts of events on driver cognitive states

The differences in cognitive states can be attributed to: (i) information, (ii) changes in driving activities, (iii) changes in non-driving activities, (iv) combinations of those factors. The baseline test is needed to capture the impact of information when driving activity is reduced to minimum. Due to low level of driving stresses, driver should be able to allocate additional cognitive resources to process information, and hence, increased value in cognitive workload and/or engagement should be observed in the baseline test run. In experimental runs, however, the level of driving stress might be higher, and thereby, real-time travel information can lead to (i) missing or ignoring of information by the driver, (ii) changes in driving performance as cognitive resourses are channeled to information processing. In these situations, small increase or no changes are expected in cognitive workload, whereas the impacts on engagement can decrease if a driver misses or ignores the information, or increase if a driver trys to process the information. In some other situations where driving stress is high enough to overwhelm a driver, the decrease in cognitive workload and/or engagement can be expected, because he/she starts to focus only on a small range of driving activity to perform safe driving and will ignore any distractions from information.

4.2 Preliminary results

For a preliminary analysis is condcuted using the data from 12 participants (3 experimental runs per a participant) who are assigned with the same information scenario to understand the impacts of real-time travel information on driver cognitive states. Average values of cognitive workload and engagement at four different time intervals (1 second before voice information and 1st, 2nd, and 3rd seconds of voice information) on a scale of 0 to 1 with 1 being the maximum cognitive workload or highest engagement are showed in Figure 18. The results indicate that the increases in both cognitive workload and engagement are observed in baseline runs (where low driving stress is expected), followed up with slight decreases in both cognitive indexes at 2nd and 3rd seconds of voice information. This implies the impacts of voice information on driver cognitive states. Another noticeable observation is that the level of engagement before voice information provision is much lower at baseline test run compared to the following experimental runs. This is probably because of monotonous driving environments of driving baseline tests due to the distraction-free characteristics (absense of traffic-related and information-related cues).

In addition, Figure 18 illustrates the impacts of voice information on driver cognitive states when driving stress is high (i.e., experimental runs). High traffic conditions are simulated in the scenarios of the experimental runs. However, the cognitive workload before the provision of voice information is very similar in both baseline runs and experimental runs, unlike the engagement values. After beginning of voice information (from 2nd second) an increase in cognitive workload and small reduction in the engagement are observed from the collected data. As cognitive workload and engagement are measurements of different cognitive processes shaing limited cognitive resources, an increase in one measurement reduces the resources available for the other. Note that the average value of engagement during the 3rd second of voice information (in experimental runs) is almost half of the value at baseline runs (1 second before the voice information), while cognitive workload has not experienced significant changes. In other words, our observations show significant decrease in driver attention as voice information begins if driving stress before voice information is already high. A decrease in engagement or driver attention can be attributed to route choice decision-making processes associated with route choice, lane choice, and other driving decisions that are executed with assistance of the information.

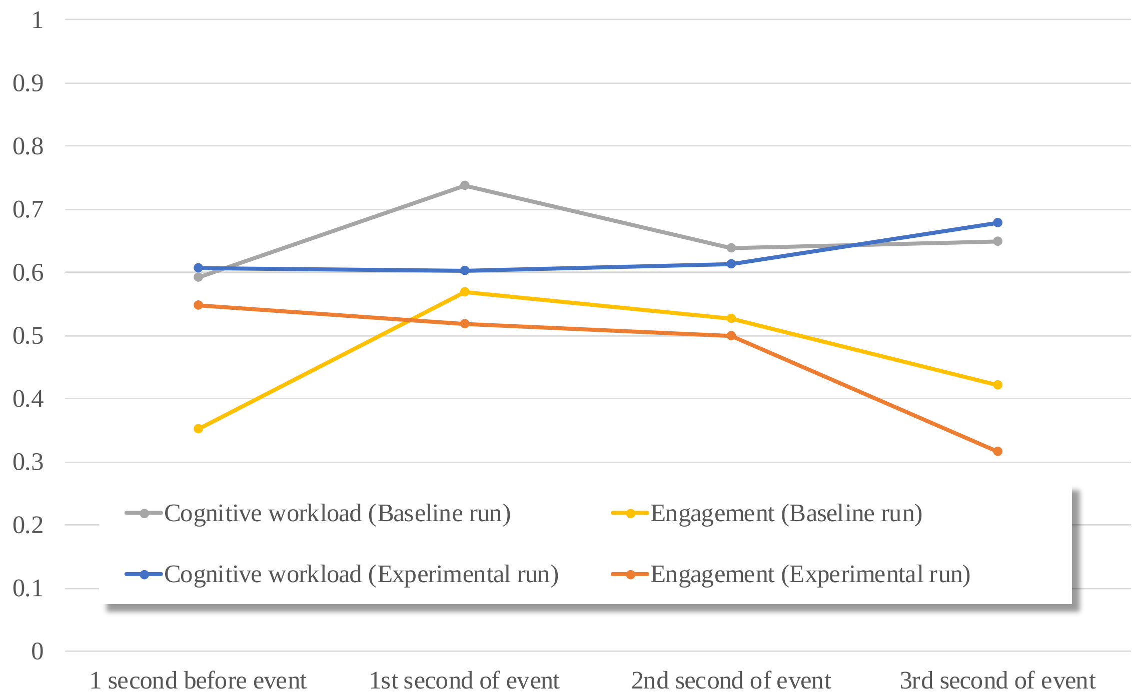

Figure 18. EEG metrics for 12 participants with same experiment scenario

Preliminary results presenting in this chapter imply that incorporating the psychophysiological sensors with IVIS can help to quantify cognitive influences of information provision (including real-time travel information) and, hence, improve the understanding of drivers' route choice decision-making behavior. It also verifies the feasibility of usage of psychophysiological sensors to monitor driver cognitive states under real-time information provision. The study results can provide infights not only for system operators in improving effectivness of real-time travel information provision strategies based on the holistic understanding of driver cognitive states, but also for car manufacturers in developing effective in-vehicle information delivery systems based on the implications of psychophysiological data.

CHAPTER 5. CONCLUSIONS AND FUTURE WORK

5.1 *Summary*

In this study, we developed and advanced an interactive driving simulator experiments to acquire the physiological data of drivers showing their perceptional and psychological states as well as their revealed route choices. The proposed interactive driving simulator experiments use a realistic road network of Indianapolis, Indiana, so that the participants configure the attraction of the routes based on not only the information but also the route attributes (e.g., freeway, number of turns, stops, length, and so on). The experiments also consider dynamic background traffic demands which are enabled by integration between driving simulator and microscopic traffic simulation package (Transport Simulation Systems, 2008). Various information scenarios with multiple disseminating sources are prepared to examine participants' perceptional and psychological states depending on different information characteristics (e.g., amount, source, or content). Lastly, HD cameras and biosensors (i.e., EEG, ECG, eye-tracker) are integrated with driving simulator experiments to collect participants' physiological data. The online coordination between the multiple biosensors, HD cameras, and driving scenario enables to understand drivers' dynamic cognitive states during the driving depending on the real-time travel information.

From the research point of view, we proposed a comprehensive structure to address traveler route choice decision-making process including psychological effects of real-time travel information and quantifiable cognitive workload. Drivers' subjective perception of information and the consequential psychological effects and benefits are analyzed through the proposed structure. Specifically, the causal relationships between the latent variables representing psychological effects of information and other traditional explanatory variables (e.g., individual attributes, travel context, information characteristics, etc.) are explored in the proposed latent variable model. Latent psychological effects of the information are inferred based on the indicator variables that reflect driver's perception of information. The analysis results imply that the consideration of perceptional and emotional aspects of different drivers with heterogeneous individual preferences, travel context and information characteristics enhances the understanding of drivers' revealed route choice behavior.

Furthermore, multiple biosensors are employed as sources of quantitative estimation of the psychophysiological aspects of driver cognitive states. The feasibility and usability of EEG, ECG and eye-tracker to infer on drivers' cognitive states are demonstrated. This study also developed a framework to use data from the eye-tracker video to capture the causation of cognitive workload and engagement levels based on EEG data. The results illustrate drivers' usage of cognitive resources in different traffic environments and indicate that drivers may not be able to process and use the information provided while driving stress is high. The study insights can aid vehicle manufacturers to design IVIS and transportation planners to develop strategies that can reduce cognitive workload for real-time travel information provision.

The key contributions of this project are in (i) demonstrating the causal relationships among the factors that construct psychological effects of real-time travel information, (ii) explicitly considering the psychological values underneath drivers' revealed route choice behavior to understand the holistic structure of the benefits of real-time travel information, and further, (iii) attempting to quantify the driver cognitive state and workload using physiological data acquired from biosensors (such as EEG, ECG, and eye-tracker) of the driving simulator experiments. The proposed modeling structure offers the ability to comprehend the overall benefits of real-time travel information provision involving explicit consideration of multiple dimensions of latent psychological effects. This can provide insights to public and/or private sector stakeholders in traveler information service market on developing performance measures for values of real-time travel information, effective design and delivery strategies of the information.

5.2 Future research directions

Despite the insightful results of the study based on the driving simulator experiment data, a few additional studies are required to improve illustration of drivers' behavior in route choice context. For example, traveler satisfaction is another critical factor to evaluate his/her own route choice decisions so that it can alter their route choices in future. The analysis of traveler satisfaction considering the psychological effects of information will be investigated to understand future route choice decisions. Moreover, potential placebo effects of real-time travel information will also be studied to address a specific situation where only psychological benefits exist without improvement in travel time. In future studies, the approach should be extended to quantify the inclusive benefits of real-time travel information as another concrete performance measure for

ATIS. Next, the integration of eye-tracker and EEG data can be further used to classify driver attitude toward information and identify information characteristics and situational factors that lead to drivers' cognitive overload. To understand and quantify causal relationships between driver cognitive states defined by biosensor data under real-time travel information provision, micro-level driving performance and driver route choice behavior, the statistical modeling approach can be used.

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