UNDERSTANDING THE COGNITIVE AND PSYCHOLOGICAL IMPACTS OF EMERGING TECHNOLOGIES ON DRIVER DECISION-MAKING USING PHYSIOLOGICAL DATA

by

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To my beloved parents and sister,

For always supporting my choices

To my dearest niece Navya,

For all the joy she brought to me

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LIST OF ABBREVIATIONS

ADS	Automated driving system
AIC	Akaike information criterion
ANOVA	Analysis of variance
AOI	Area of interest
ATIS	Advanced traveler information systems
AV	Automated vehicle
ECG	Electrocardiogram
EEG	Electroencephalogram
GPS	Global position system
HR	Heart rate
IVIS	In-vehicle information system
LMM	Linear mixed model
MIMIC	Multiple indicators multiple causes
NDRT	Non-driving related task
NHR	Normalized heart rate
OGR	On-road glance rate
PSD	Power spectral density
RAR	Road attention ratio
SA	Situational awareness
SAE	Society of Automotive Engineers
SEM	Structural equation model

TOPI	Takeover Performance Index (TOPI)
TOR	Takeover request
TTC	Time-to-collision
VMS	Variable message sign

ABSTRACT

Emerging technologies such as real-time travel information systems and automated vehicles (AVs) have profound impacts on driver decision-making behavior. While they generally have positive impacts by enabling drivers to make more informed decisions or by reducing their driving effort, there are several concerns related to inadequate consideration of cognitive and psychological aspects in their design. In this context, this dissertation analyzes different aspects of driver cognition and psychology that arise from drivers' interactions with these technologies using physiological data collected in two sets of driving simulator experiments.

This research analyzes the latent cognitive and psychological effects of real-time travel information using electroencephalogram (EEG) data measured in the first set of driving simulator experiments. Using insights from the previous analysis, a hybrid route choice modeling framework is proposed that incorporates the impacts of the latent information-induced cognitive and psychological effects along with other explanatory variables that can be measured directly (i.e., route characteristics, information characteristics, driver attributes, and situational factors) on drivers' route choice decisions. EEG data is analyzed to extract two latent cognitive variables that capture the driver's cognitive effort during and immediately after the information provision, and cognitive inattention before implementing the route choice decision.

Several safety concerns emerge for the transition of control from the automated driving system to a human driver after the vehicle issues a takeover warning under conditional vehicle automation (SAE Level 3). In this context, this study investigates the impacts of driver's pre-warning cognitive state on takeover performance (i.e., driving performance while resuming manual control) using EEG data measured in the second set of driving simulator experiments. However, there is no comprehensive metric available in the literature that could be used to benchmark the role of driver's pre-warning cognitive state on takeover performance, as most existing studies ignore the interdependencies between the associated driving performance indicators by analyzing them independently. This study proposes a novel comprehensive takeover performance metric, Takeover Performance Index (TOPI), that combines multiple driving performance indicators representing different aspects of takeover performance.

Acknowledging the practical limitations of EEG data to have real-world applications, this dissertation evaluates the driver's situational awareness (SA) and mental stress using eye-tracking

and heart rate measures, respectively, that can be obtained from in-vehicle driver monitoring systems in real-time. The differences in SA and mental stress over time, their correlations, and their impacts on the TOPI are analyzed to evaluate the efficacy of using eye-tracking and heart rate measures for estimating the overall takeover performance in conditionally AVs.

The study findings can assist information service providers and auto manufacturers to incorporate driver cognition and psychology in designing safer real-time information and their delivery systems. They can also aid traffic operators to incorporate cognitive aspects while devising strategies for designing and disseminating real-time travel information to influence drivers' route choices. Further, the study findings provide valuable insights to design operating and licensing strategies, and regulations for conditionally automated vehicles. They can also assist auto manufacturers in designing integrated in-vehicle driver monitoring and warning systems that enhance road safety and user experience.

1. INTRODUCTION

1.1 Background and motivation

Emerging technologies such as real-time travel information systems and automated vehicles (AVs) have profound impacts on driver decision-making behavior and the overall transportation system. Real-time travel information from advanced traveler information systems (ATIS) assists drivers in making more informed travel choices (Ben-Elia & Avineri, 2015; Yu & Peeta, 2011). It enables traffic operators and transportation planners to design and deploy effective traffic management strategies to alleviate traffic congestion by predicting drivers' route choice decisions under information provision (Paz & Peeta, 2008, 2009a). Similarly, partially AVs (SAE Level 2) can substantially reduce drivers' effort by assisting them with lane-keeping and/or adaptive cruise control (SAE J3016, 2018). As vehicle automation technologies mature to conditional automation (SAE Level 3), drivers will assume an even more passive role in the dynamic driving task and will be able to engage in non-driving related tasks (NDRTs) that can make the trip more leisurely and/or productive. AVs will also enhance road safety by reducing the possibility of human error, which often results from distraction or fatigue (Chao & Kratsios, 2020).

Advances in information and communication technologies have substantially increased the amount, complexity, and diversity of real-time travel information available to drivers through multiple sources such as personal devices and public infrastructure. While it generally has positive impacts, poorly-designed information and associated delivery systems can lead to information-induced cognitive overload, distraction, and detrimental psychological effects, which can lead to reduced road safety, user experience, and trust in information systems (Abe & Richardson, 2006; Birrell & Young, 2011; Green, 2000). Previous studies have proposed route choice models under real-time information provision that incorporate factors such as route characteristics (e.g., driving environment complexity), driver attributes (e.g., sociodemographic characteristics and inherent behavior/attitudes), situational factors (e.g., traffic congestion), and information characteristics (e.g., amount, content, and quality) (Ben-Elia et al., 2013; Paz & Peeta, 2009a; Peeta et al., 2000; Peeta & Yu, 2002, 2004; Polydoropoulou et al., 1996). However, most of these models assume that drivers are able to seamlessly perceive, process, and utilize the information, and thereby, do not consider the impacts of information-induced cognitive effects on the decision-making process.

Some studies have captured the role of information behavior, information processing capability, and psychological effects of information on drivers' routing decisions (Hato et al., 1999; Prato et al., 2012; Song et al., 2017), but they do not explicitly consider the cognitive effects (e.g., increased alertness and cognitive processing) of interacting with real-time information. Hence, it is critical to understand the cognitive and psychological effects of real-time information to enhance road safety and user experience, and to incorporate them in route choice modeling under real-time travel information provision to improve the reliability of drivers' route choices, and thereby, network traffic flow predictions.

AV technologies can make driving less stressful both physically and cognitively. However, under relatively lower levels of automation capabilities, in which some (Level 2) or all aspects (Level 3) of the dynamic driving task are controlled, a driver will be required to resume manual control of the vehicle as a fallback option if it issues a takeover warning for venturing out of its operational or for experiencing a system failure. However, several concerns loom over the driver's ability to respond to such warnings and their takeover performance (i.e., driving performance while resuming manual control) in partially AVs due to mental underload and passive fatigue after a sustained period of automated driving (Körber et al., 2015; Young & Stanton, 2002). Additional concerns arise regarding NDRT-induced driver distraction and reduced situational awareness under conditional automation (Capalar & Olaverri-Monreal, 2018; Radlmayr et al., 2014). Hence, to design better takeover warning systems and enhance road safety, it is important to evaluate the impacts of driver's cognitive state on takeover performance under conditional automation. Further, most existing studies evaluate takeover performance by analyzing multiple driving performance indicators (e.g., minimum time-to-collision and maximum deceleration) independently, thereby ignoring their interdependencies. Therefore, there is a need for a single comprehensive metric that captures such interdependencies and can be used to benchmark the impacts of driver's cognitive state on the overall takeover performance.

Previous studies have estimated the latent cognitive and psychological aspects of the aforementioned emerging technologies on drivers using subjective self-reported data (Hato et al., 1999; Körber et al., 2015; Prato et al., 2012). However, self-reported data can be limited by several memory and reporting biases (e.g., misattribution and transience) (Schacter, 1999; van de Mortel, 2008). In the context of information systems, some studies have also used indirect objective measures such as driving and secondary task performance to assess driver cognition (Coleman et al., 2016; Jamson & Merat, 2005); however, they mainly inform on the level of distraction or workload due to the secondary task or are unable to differentiate between inattention towards information and the ease of perception and processing information. Some studies have also used expert rater assessment to estimate driver's cognitive state (Naujoks et al., 2018); however, these methods are prone to errors arising from their subjective nature, such as the halo effect (Engelhard Jr, 1994). Recent advances in biosensing technologies and driver monitoring systems provide capabilities to evaluate of different aspects driver's cognitive and psychological aspects using physiological indicators (e.g., brain electrical activities, eye gaze patterns, and heart rate) that can be measured directly and non-intrusively. Previous studies have linked various trends in different physiological indicators with different cognitive and psychological processes (e.g., increase in heart rate indicates higher mental stress) (Abhang et al., 2016b; Almahasneh et al., 2014; Merat et al., 2012; Ignacio Solís-Marcos et al., 2017; Taelman et al., 2008). Hence, physiological indicators can avoid the limitations of subjective data and indirect objective measures as discussed above to estimate driver's cognitive and psychological states. However, physiological indicators typically tradeoff between their practicality for real-world applications and the granularity of analysis. For example, although electroencephalogram (EEG) data allows for more detailed analysis in laboratory settings compared to eye-tracking and electrocardiogram (ECG) data (Berka et al., 2007; Wilson, 2002), it is less practical to use EEG in the operational context. This dissertation uses EEG data to provide detailed insights for the design and planning context, and eye-tracking and ECG data to develop real-world applications.

1.2 Research objectives and tasks

This dissertation has two major objectives arising from the impending roles of emerging technologies in the transportation domain.

1. The dissertation seeks to examine the latent cognitive and psychological effects of real-time travel information and analyze their impacts on drivers' route decision-making process. It analyzes drivers' objective physiological data (EEG) to estimate a detailed profile of the latent information-induced cognitive and psychological effects. The following tasks are performed to achieve this objective:
    - Driving simulator experiments with a network-level setup featuring two routes with different characteristics (i.e., driving environment complexity) and dynamic ambient traffic

are designed. This creates a realistic driving experience and route choice decision-making context for the study participants, where their route choices have considerable impacts on their travel times and the disseminated real-time travel information can help them to potentially reduce their travel times.

- Experiment scenarios are created to capture the effects of real-time travel information characteristics (i.e., source, amount, content, and sufficiency) and situational factors (i.e., traffic congestion) on driver cognition and psychology, and their combined impacts on route choices.
- Novel mechanisms are implemented to elicit intent from the participants to reach the destination on time by providing them with a driving objective (i.e., morning commute trip) and compensating them using a point-based reward system that tracks their intent to complete the trip within the assigned time while executing safe driving actions.
- Brain electrical activity patterns of each participant are measured non-intrusively using an EEG in three experiment runs. Raw EEG signals are preprocessed by decontaminating the low- and high-frequency noise and by computing EEG band powers in four frequency bands. A comprehensive review of the neuroscience and related literature is performed in the context of the study objectives to link EEG band powers in different regions of the brain to latent cognitive and psychological processes.
- The impacts of real-time auditory travel information characteristics and route characteristics on driver's cognition and psychology are analyzed using the EEG band powers during and immediately after the information provision.
- A hybrid route choice model is proposed that incorporates the latent cognitive effects (e.g., cognitive effort and attentional resources) of real-time travel information along with several explanatory variables that can be measured directly, including route characteristics, driver attributes, situational factors, and information characteristics. The latent cognitive effects are estimated using the EEG band powers during and immediately after the information provision, and the EEG band powers immediately before the route choice location. The model simultaneously analyzes the effects of explanatory factors on the latent cognitive effects and incorporates their combined impacts on drivers' route choices.

2. The dissertation seeks to benchmark the effects of drivers' cognitive states on takeover performance under conditional automation. It estimates drivers' cognitive states using two sets

of physiological data that complement each other in terms of the granularity of cognitive analysis (EEG) and the practicality for real-world applications (eye-tracker and ECG). Further, a lack of a comprehensive takeover performance metric in the literature motivate the objective of proposing a single comprehensive metric that combines multiple driving performance indicators, and can be used to benchmark the effects of driver cognition on the overall takeover performance. The specific tasks related to this objective are as follows:

- Driving simulator experiments are designed with an automated driving system (ADS) that mimics a conditionally AV. A four-lane divided highway replicating the road curvatures of the U.S. Interstate 65 is created in the simulator to potentially enhance the ecological validity of the study.
- Three experiment runs are created to replicate different safety-critical events providing two types of takeover warnings (mandatory vs. non-mandatory takeover).
- A non-driving related task (NDRT) is developed to simulate visual and manual distraction for the participant and to disengage them from the driving task, which is expected in conditionally AVs. To further provide an incentive to disengage from driving and engage in the NDRT, participants are informed that their compensation would depend on the correct NDRT responses and road safety across all three runs.
- EEG data is collected and preprocessed using the same methods described earlier. In addition, heart rate using an ECG and eye gaze patterns using wearable eye-tracking glasses are also measured. Heart rate data is normalized for each participant over all three runs to alleviate the individual differences. On-road glance rate and road attention ratio during the automated drive are extracted from the eye gaze patterns.
- A novel comprehensive takeover performance metric, Takeover Performance Index (TOPI), is proposed. The TOPI combines multiple driving performance indicators representing different aspects of takeover performance while partly accounting for their interdependencies.
- The driver's pre-warning cognitive state is estimated using EEG band powers immediately before the takeover warning. The impacts of driver's pre-warning cognitive state, age, driving experiences, novelty in takeover experience, and type of takeover warning are benchmarked on the overall takeover performance using the TOPI.

- The driver's situational awareness (SA) during the automated drive and mental stress before/after the takeover warning are estimated using eye-tracking and heart rate measures, respectively, that can be obtained from in-vehicle driver monitoring systems. The study analyzes the differences in driver's SA and mental stress over time (i.e., successive takeover situation experiences) and their impacts on the TOPI. It also examines the correlations between eye-tracking and heart rate measures to investigate the relationship between SA and mental stress in conditionally AVs.

1.3 Research overview

This dissertation examines multiple aspects of driver cognition and psychology using objective physiological data, under real-time travel information provision and in conditionally AVs, and incorporates them in modeling the driver's decision-making process and corresponding driving performance.

The first part of this dissertation analyzes the latent cognitive and psychological effects of real-time auditory travel information using EEG data, by drawing insights from the neuroscience domain. Driving simulator experiments with a network-level setup and dynamic ambient traffic are designed to create a realistic driving experience, and thereby capture the interactive cognitive impacts of driving environment complexity and real-time information characteristics. A comprehensive analysis of several factors (i.e., information characteristics, time stages of interaction with information, and driving environment) that impact the cognitive and psychological effects of real-time travel information is provided.

Using insights from the previous analysis, a hybrid route choice modeling framework is proposed that incorporates the latent information-induced cognitive effects (estimated using EEG data) along with other explanatory variables that can be measured directly (i.e., route characteristics, information characteristics, driver attributes, and situational factors) to predict route choice decisions under real-time information. The impacts of two latent cognitive effects on the route choice behavior are discussed: (i) cognitive effort to process and perceive real-time information, and (ii) cognitive inattention towards the road environment.

Unlike real-time travel information, drivers' decisions and responses to takeover warnings in AVs have immediate repercussions on road safety. The next part of the dissertation analyzes the impacts of driver's pre-warning cognitive state on their takeover performance in conditionally AVs.

Similar to our previous work, EEG data is analyzed to estimate a detailed profile of driver's pre-warning cognitive state. A novel comprehensive takeover performance metric TOPI is proposed to benchmark the aforementioned impacts on the overall takeover performance. The effects of individual characteristics (age and driving experience), novelty in takeover experience, and type of takeover warning are also analyzed on the TOPI.

Acknowledging the practical limitations of measuring EEG data in real-world driver monitoring systems applications, this dissertation evaluates the driver's SA and mental stress using eye-tracking and heart rate measures, respectively, that can be obtained from in-vehicle driver monitoring systems in real-time. The differences in SA and mental stress over time (i.e., successive takeover experiences), their correlations, and their impacts on the TOPI are analyzed to evaluate the efficacy of using eye-tracking and heart rate measures for estimating the overall takeover performance in conditionally AVs.

1.4 Dissertation structure

This dissertation consists of six chapters. Chapter 2 presents the research on investigating the cognitive effects of real-time auditory travel information using EEG data. The impacts of route characteristics, information characteristics, and time stages of interaction with information provision on physiological manifestations of driver cognition and psychology are discussed. The study results provide insights for information service providers to factor cognitive aspects while designing information and its delivery systems.

Chapter 3 proposes a hybrid route choice model under real-time information provision. Latent cognitive and psychological effects induced by information provision are estimated using EEG data. The proposed model can simultaneously predict latent effects from other explanatory factors and model their combined impacts on drivers' route choices. The study results illustrate the importance of considering latent cognitive and psychological effects in modeling route choice under information provision. They also provide valuable insights for multiple stakeholders, including traffic system operators, information service providers, auto manufacturers, and transportation planners.

Chapter 4 estimates a detailed profile of driver's pre-warning cognitive state using EEG data and analyzes its impacts on takeover performance in conditionally AVs. It also presents a novel framework to compute a comprehensive takeover performance TOPI to benchmark the effects of pre- warning driver's cognitive state on the overall takeover performance. The study results illustrate the interaction effects of driver's pre-warning cognitive state with individual characteristics, which provide valuable insights for policymakers and auto manufacturers.

Chapter 5 estimates driver's SA and mental stress using eye-tracking and heart rate measures that can be measured using in-vehicle driver monitoring systems, and thereby, evaluating their efficacy for real-world applications. It discusses the statistical analysis methods used to evaluate the differences in driver's SA and mental stress over time, their correlations, and their impacts on takeover performance. The study results provide insights for auto manufactures and driver monitoring system designers to develop integrated driver monitoring and warnings systems.

Chapter 6 summarizes the contributions of this work. It discusses the study findings and insights, and concludes the dissertation by providing some future research directions.

2. EVALUATING THE COGNITIVE AND PSYCHOLOGICAL EFFECTS OF REAL-TIME AUDITORY TRAVEL INFORMATION ON DRIVERS USING EEG

2.1 Introduction

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

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

Several studies have evaluated the impacts of information provision on driver decision-making behavior and driving performance. Most existing driver behavior models under real-time information provision capture the impacts of road/route characteristics, generalized travel costs (for example, travel time and fuel consumption), heterogeneity in individual characteristics (for example, age and trip purpose), and real-time information characteristics (for example, amount and content) (Agrawal et al., 2016; Ben-Elia et al., 2013; Bonsall, 1992; Dia, 2002; Han et al., 2013; Peeta et al., 2000; Peeta & Yu, 2002, 2004). Some route choice models capture the role of information accuracy (Ben-Elia et al., 2013), multiple information sources (Hato et al., 1999), and past experience with information (Ben-Elia et al., 2008). Others analyze the compliance of drivers towards real-time travel information (Chen et al., 1999; Srinivasan & Mahmassani, 2000), and the heterogeneity in value of real-time travel information for drivers (Chorus et al., 2006; K. Kim & Vandebona, 1999; L. Zhang & 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 & Gao, 2013), and regret theory (Chorus et al., 2008), to capture the heterogeneity in decision-making. Paz and Peeta (2008, 2009a, 2009b, 2009c) developed traffic routing models under real-time travel information provision that are consistent with drivers' behavioral responses (for example, compliance) towards different information characteristics. However, the aforementioned models often assume seamless perception, processing, and utilization of real-time information by drivers in an already cognition-heavy driving task. Thereby, they ignore information-induced cognitive load and task demand (for example, attention to internal processing, memory retrieval, and memory processing) that can increase driver distraction and/or reduce the utilization of real-time information in making routing decisions. This is important because such cognitive aspects can deteriorate driving performance and reduce road safety. In addition, these models do not explicitly consider the psychological effects (for example, stress and anxiety) of information content (for example, route recommendations or unfavorable travel information) that may impact drivers' route choice decision-making process.

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

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

Advances in biosensing technologies and driver monitoring systems have provided capabilities for unobtrusive, real-time driver psychophysiological analysis. Past studies have developed methods to estimate driver’s level of attention and mental workload associated with information systems using physiological factors such as eye blink/gaze behavior (Benedetto et al., 2011; Faure et al., 2016), heart rate (Heine et al., 2017; Tjolleng et al., 2017), brain electrical activity (Berka et al., 2005), facial expressions, or a combination thereof (Haak et al., 2009; Ji et al., 2004). Further, there is a growing consensus that brain electrical activity data collected using EEG provides better estimates of human attention compared to other physiological data such as functional magnetic resonance imaging (fMRI), functional near-infrared (fNIR) spectroscopy, galvanic skin response, heart rate variability, and pupillometry (Berka et al., 2007; Wilson, 2002). The localization of the physiological manifestations of different cognitive and psychological states in different regions of the brain allows for a more detailed analysis compared to other physiological indicators. However, most existing EEG studies in the driving context are limited to assessing driver fatigue (Gharagozlou et al., 2015; Jagannath & 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). Very few efforts have been made to model driver behavioral aspects using EEG. For example, Yang et al. (2018) developed a classification algorithm for driving aggressiveness and stability based on EEG measures. Even these studies use oversimplified driving environments (in terms of traffic interactions and road characteristics) and, therefore, do not account for the differences in the cognitive effort required to drive in environments with different complexities while interacting with real-time information delivery systems. This study bridges this critical gap by implementing a network-level driving simulator environment with real-world dynamic traffic characteristics to analyze the cognitive and psychological effects of driving environment complexity and auditory real-time travel information by analyzing EEG data. Further, our experiment design elicits realistic attitudes and behaviors towards real-time information from the participants by enabling intent through novel compensation mechanisms (please see details in Section 2.2.3) and ensuring that route choices have perceptible impacts on their travel time.

To design safe and effective real-time information and their delivery systems, it is critical to understand the cognitive and psychological impacts of real-time information systems for the following reasons: (i) drivers' cognitive efforts (for example, internal processing, memory retrieval, and memory processing) to perceive and process information impact its utilization in making route choice decisions, (ii) changes in drivers' cognitive states (for example, distraction and inattention) can have considerable impacts on driving performance that may affect road/driver safety, and (iii) changes in psychological states (for example, anxiety and stress) can impact drivers' routing decisions and have direct implications for the evolution of traffic network flows. In this context, this study analyzes the latent cognitive and psychological effects of different real-time auditory travel information characteristics, including amount (i.e., the units of information in a message provided to the driver) (Dudek, 2004), sufficiency (sufficient vs. insufficient), and content (descriptive travel times vs. prescriptive route recommendation) in the different time stages of interaction with information provision (before, during, and after). In this study, sufficient information means that the drivers are provided information on the current and alternative routes, while insufficient information corresponds to no information on the alternative route. We also investigate these latent effects on routes (freeway and arterial) with different driving environment complexities in terms of road characteristics, traffic interactions, and travel time uncertainty. Further, we analyze drivers' brain electrical activity patterns using EEG to investigate multiple aspects of information-induced cognitive and psychological effects that are associated with different regions of the brain. The study results and insights can aid information providers and auto manufacturers to incorporate driver cognition in designing real-time information systems to enhance road safety and improve user experience. They also enable the development of improved hybrid driver behavior models that factor the cognitive and psychological effects of real-time information provision.

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

The remainder of the paper is organized as follows. Section 2.2 discusses the driving simulator and accessory equipment used, experiment design, implementation procedure, data collection, and data analysis methods. Section 2.3 discusses the analysis results. Finally, Section 2.4 concludes the paper by summarizing the study findings and limitations and providing future research directions.

2.2 Methodology

2.2.1 Driving Simulator

This study uses a fixed-base driving simulator featuring a full-scale driving cockpit with automatic gear box, turn signals, and steering wheel with force feedback. A network-level setup that replicates the northern loop in Indianapolis, Indiana is created using OKTAL SCANeRStudio® 1.4 software (OKTAL, 2017). The driving environment is projected on three wide LCD screens that provide a field-of-view of around 120 degrees. As illustrated in Figure 2.1, the drivers (study participants) can choose between two routes, freeway (blue) and arterial (yellow), to reach their destination, and have two potential locations to switch routes during the trip. To ensure a realistic driving environment, a microscopic traffic simulator (AIMSUN 6.2) is integrated in real-time with the driving simulator to generate dynamic and responsive ambient traffic consistent with two traffic condition scenarios (with and without road accident). The two routes have different driving environment complexity in terms of the speed limit, number of intersections/interchanges, density of road objects (for example, street name sign or traffic signal), and traffic interactions. Further, the larger driving environment complexity of the arterial route results in larger travel time uncertainty compared to the freeway route. This enables analyzing the differences between the cognitive and psychological effects of different real-time travel information characteristics on routes with different complexity. A road network map displaying the drivable roads in grey and the participant vehicle's current GPS location in the simulator is provided on a tablet screen that is placed on the simulator dashboard as illustrated in Figure 2.2. Each route has two auditory personalized travel information (i.e., information customized to the destination) provision locations and two accident locations (as illustrated in Figure 2.1). Freeway route also has provisions for visual public travel information (i.e., information to specific landmarks on the road network) via variable message signs (VMSs), which are located beyond the locations at which auditory information is provided. The maximum number of accidents in each experiment run is set to one.

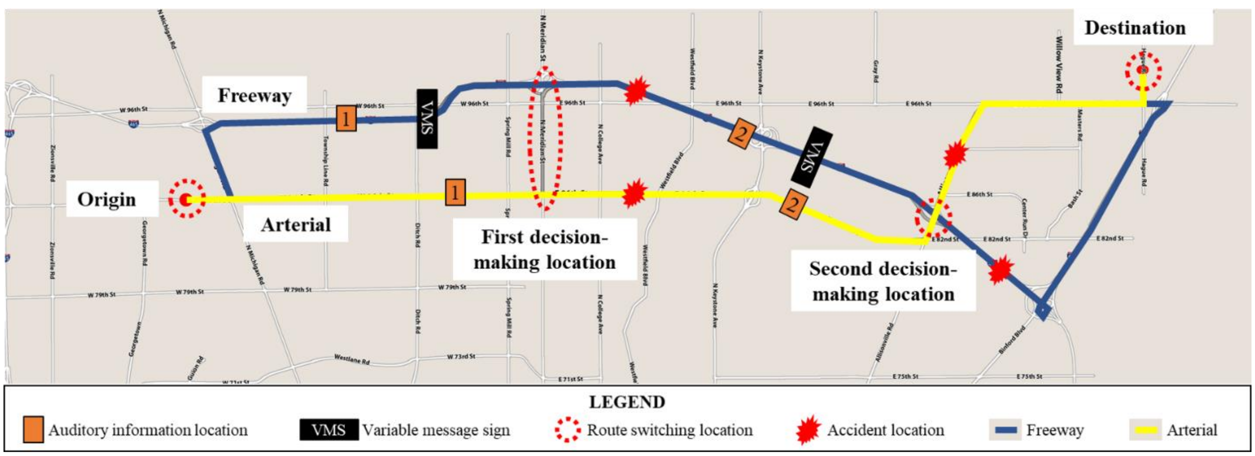

Figure 2.1 Experiment network setup illustrating real-time information provision locations

2.2.2 Scenario Design

Four auditory real-time travel information provision scenarios are created. They include: (i) no information (NI), (ii) travel time on current route (CT), (iii) travel times on current route and alternative route (AT), and (iv) prescriptive information informing drivers about downstream congestion and recommending alternative route (PI). CT provides insufficient travel information to the drivers; that is, no information is provided on the alternative route or route recommendation. PI is available only in scenarios with road accident. The information is delivered through multimedia speakers positioned on each side of the driving cockpit below the screens. The auditory information is repeated (i.e., two instances of same information) immediately after the first instance to provide an additional opportunity to the participants in case they miss the first instance. Each scenario is characterized by different amount (i.e., the units of information in a message provided to the driver), sufficiency (sufficient vs. insufficient), and content (descriptive travel times vs. prescriptive route recommendation) of information to investigate the cognitive (for example, increased attention to internal processing, memory retrieval, and distraction) and psychological (for example, increased anxiety and stress levels) impacts of real-time travel information on drivers. The information scenarios are designed such that the alternative route is either more attractive due to longer travel time on the current route or is recommended by the information due to downstream congestion on the current route. This study uses data only near the first auditory information provision location (labeled as “1” in Figure 2.1) to avoid the interaction effects associated with multiple sources of information on freeways (i.e., personalized and public) and the multiple times real-time information is provided during a single trip.

Figure 2.2 Driving simulator

2.2.3 Participants

The study participants were recruited from the Greater Lafayette, IN community through advertisements in a university-wide email newsletter (at Purdue University), paper fliers, and word of mouth. The following criteria were used to recruit participants: (1) being 18 years of age or older, (2) having a valid driver’s license, (3) not wearing corrective glasses (as we also collected eye tracking data using wearable glasses), (4) having no predisposition to motion sickness, and (5) not self-reporting physical or mental impairments. Potential participants signed up for an on-site simulator experiment session at the study experiment website by providing the requested information. Since certain medications and caffeine ingestion can affect EEG patterns (Blume, 2006; Pritchard et al., 1995) and, thereby, EEG data quality, participants were asked to not consume any medication or caffeine for at least 8 hours prior to the experiment. All recruited participants self-reported no medication or caffeine ingestion within the stated time period.

Participants arriving for the driving simulator session were first familiarized with the simulator environment through a practice run on the network setup shown in Figure 2.1. Those showing motion sickness at this stage were not allowed to proceed further. Participants were informed that the freeway route is 16 miles long and it takes 21 minutes, on average, to reach destination under normal traffic conditions, while the arterial route is 11 miles long but takes about 25 minutes under normal conditions. The practice run started from the intersection before the first information provision location on the arterial route. During the run, participants were instructed to switch to the freeway route at the first decision-making location and then switch back to the arterial route at the second decision-making location. The run ended soon after the participant went past the second decision-making location. Through the practice run, a basic level of familiarity with the road network and information sources was created for all participants. Fast-forwarded driving videos of both routes were shown to each participant, with several pauses to illustrate important sign boards and turns to enhance familiarity with the study network. Next, participants were equipped with the EEG and completed an EEG baseline test in the B-Alert software (B-Alert, 2009) in a quiet room. After the test, they were equipped with wearable eye tracking glasses. To verify EEG data acquisition, participants completed another simulated run following simple on-screen instructions (for example, “stay in the middle lane” and “maintain speed limit”). Then, each participant was asked to execute three simulator runs from the origin to the destination using randomly-assigned information scenarios. Participants were instructed to drive as if they were commuting to work, and compensated up to $60 using a point-based reward system that tracked their intent to complete the trip within the assigned time limit (that is, the work start time) and their compliance with traffic rules and safe driving actions. They were aware of the maximum compensation for the study, and that reward and penalty points would be based on their intent to meet the work start time and their driving actions. However, they were not aware and, hence, could not track the actual points gained or lost with time at any point of the experiment runs.

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 2.2.3) 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 2.3. Figure 2.4 illustrates the distribution of information scenarios grouped by the route traveled at the first information provision location for all experiment runs.

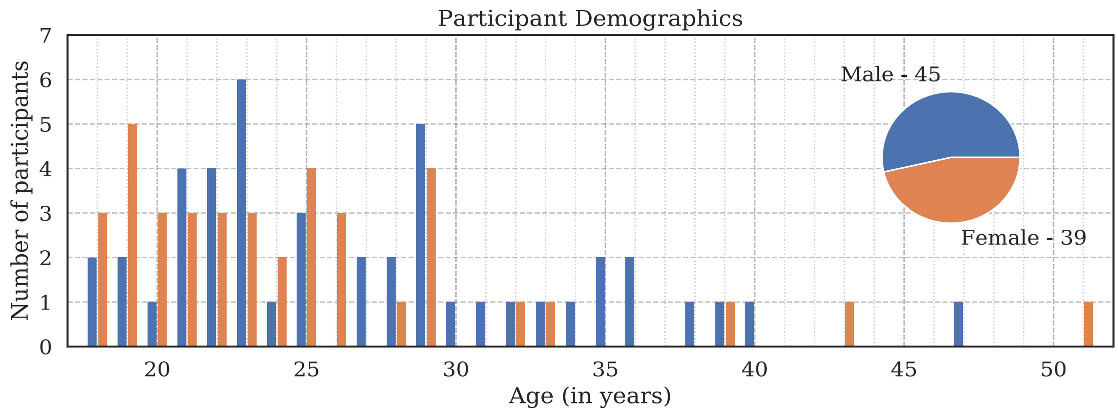

Figure 2.3 Participant age and gender distribution

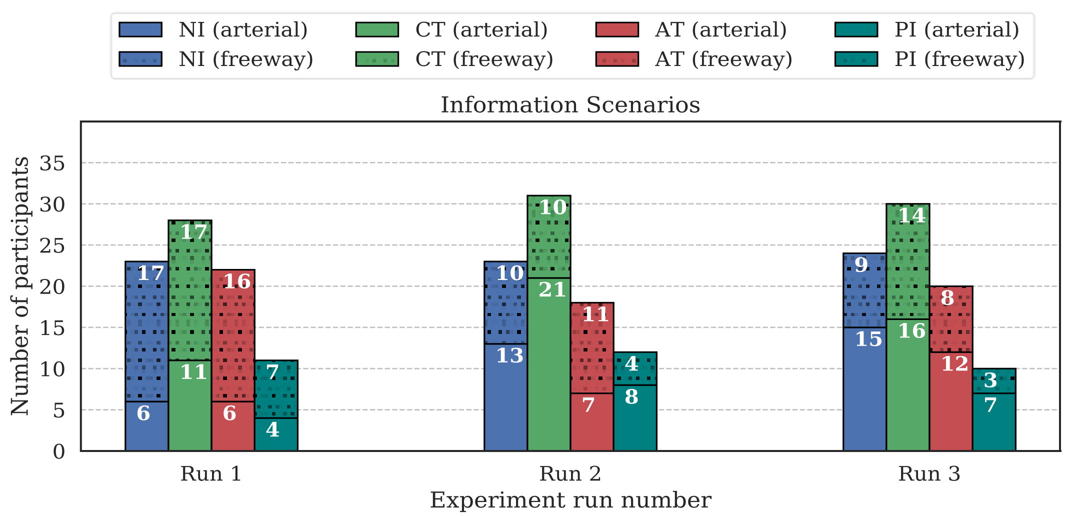

Figure 2.4 Information scenario distribution by route and experiment run

2.2.4 Electroencephalogram (EEG)

EEG measures the underlying electrical activity of the brain, mainly cerebrum, using electrodes (small metal disks) that are placed on the scalp. The cerebrum is the largest portion of the human brain and can be divided into four regions/lobes as illustrated in Figure 2.5: frontal, parietal (or centroparietal), temporal and occipital. The functionalities of each brain lobe have been extensively discussed in the neuroscience literature. The frontal lobe plays an important role in task planning, working memory, attention, and language articulation (Chayer & Freedman, 2001). It also shares the semantic and syntactic processing of auditory information with the temporal lobe (Friederici, 2011). The parietal lobe is associated with verbal-semantic processes (Doppelmayr et al., 2005) and visual attention (Bisley & Goldberg, 2010). The parietal and frontal lobes are also responsible for body motor functions (Marcus & Jacobson, 2011). The temporal lobe is generally associated with auditory information perception, memory, and language interpretation, while the occipital lobe is associated with visual information processing (Abhang et al., 2016a).

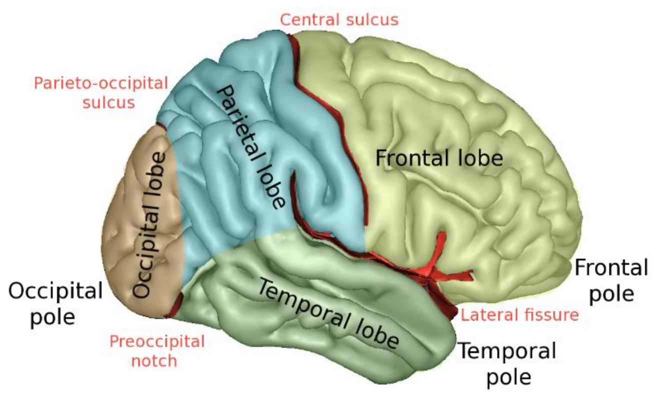

Figure 2.5 Human brain anatomy (Wikipedia, 2020)

Data on drivers' brain electrical activity is collected using a B-Alert X24 EEG system (Advanced Brain Monitoring (ABM), 2017). The EEG electrodes (also known as *EEG channels*) were placed according to the International 10-20 system as shown in Figure 2.6 (Klem et al., 1999). The brain regions and their corresponding EEG channels are shown in Table 2.1. The mastoids are used as a reference for measuring electrical signal. The data is collected using a sampling rate of 256 Hz.

Table 2.1 Brain regions and corresponding EEG channels

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

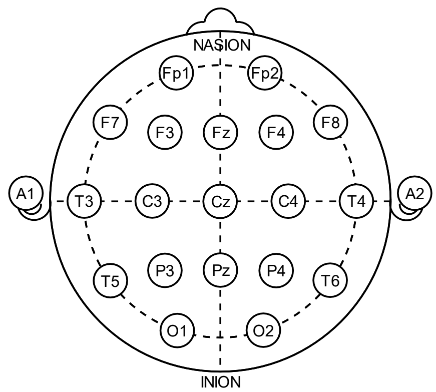

Figure 2.6 EEG electrode locations as per International 10-20 System (Wikipedia, 2019)

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). The EEG signal is then divided into epochs of 1-second duration, and power spectral density (PSD) (i.e., decomposition of signal power over a frequency range) of each epoch is computed by performing fast Fourier transformation. Next, the PSD for each epoch is averaged over 3 epochs by applying a 50% overlapping window to smoothen the data. This study analyzes the EEG signal power within four frequency bands (also known as *EEG bands*): delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz) and beta (13-30 Hz). The signal power of each band is calculated by averaging the PSD within its frequency bandwidth. Four time windows around the information provision location are defined to evaluate the information impacts at different time stages of interaction as illustrated in Figure 2.7: (i) 10 seconds before the information provision (t_0), (ii) first instance of the information (t_1), (iii) second instance of the information (t_2), and (iv) 10 seconds after the information (t_3). The information time length varies between 5 to 10 seconds depending on the scenario. The average log-power of every band (hereafter referred to as *band power*) for each time window is computed by averaging respective 1-second epoch band powers.

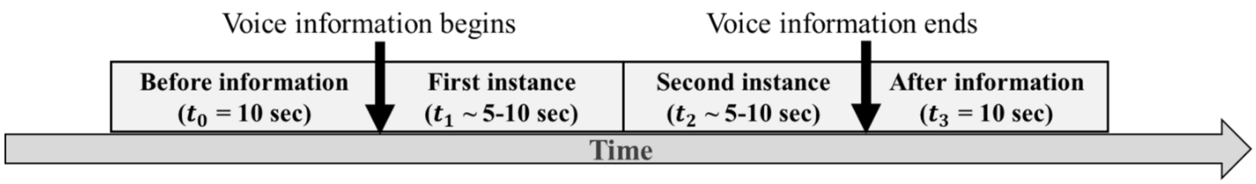

Figure 2.7 Time windows in the vicinity of the information provision location

In addition to being linked to the functionalities of each brain lobe, the EEG band powers are also associated with certain cognitive and psychological processes. The delta band power is most prominent when a person is in deep sleep (Abhang et al., 2016b). But in a wakeful state, such as when driving, the delta band power increases with increased attention to internal processing and/or memory retrieval (from long-term memory) by temporarily suppressing non-relevant neural activities related to external perception (Harmony, 2013; Harmony et al., 1996). Similar to the delta band, higher theta band power is generally associated with drowsiness and fatigue (Brown et al., 2013; Craig et al., 2012; Klimesch, 1999), but it also increases when subjected to tasks that involve inward focus (Abhang et al., 2016b) and memory processing (in short-term memory) (Aftanas & Golocheikine, 2001; Klimesch, 1999). Thus, we expect that processing real-time travel information and information from road signs, and contextualizing it in relation to the trip would evoke higher delta and theta band powers as they require higher *task demand* (i.e., increased attention to internal processing, memory retrieval and memory processing). A higher alpha band power is associated with passive attention or relaxed state of mind (Abhang et al., 2016b), while a lower alpha band power indicates increased alertness/vigilance and expectancy (Aftanas & Golocheikine, 2001), simple memory tasks (Harmony, 2013), and sensory-intake tasks that require processing external stimuli (for example, auditory information) (Ray & Cole, 1985). Foxe et al. (1998) found higher alpha activity in the parieto-occipital region under the anticipation of auditory information, suggesting a temporary disengaging of the visual attentional system. The beta band power increases with psychological stress and anxiety (Abhang et al., 2016b). It is also found to be higher under cognitive states such as focused attention to external stimulus (Abhang et al., 2016b) and increased arousal (Morales et al., 2017). Almahasneh et al. (2014) reported that drivers who are distracted by semantic tasks (for example, travel information perception) exhibit lower beta band power.

2.2.5 Data Analysis

Linear mixed models (LMMs; also known as *multilevel models*) are used to analyze the differences in band powers for each EEG channel (19 channels), EEG band (4 bands), run (3 runs), and route (2 routes). Unlike simple linear models, LMMs can analyze data with non-independent or correlated errors due to the underlying hierarchical structure in the data as would arise from repeated measurements involving each participant. LMMs incorporate both fixed effects (parameter does not vary) and random effects (parameter is treated as a random variable). In this study, fixed effects include information scenarios, time windows, and their interactions. Band powers in multiple time windows for each participant are modeled as dependent variables with normally distributed errors. No information scenario (NI) and pre-information time period (t_0) are chosen as references for information scenarios and time windows, respectively. The basic LMM form is as follows:

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

where bp denotes the band power as dependent variable, β_0 is the intercept, β_{info} is the coefficient for information scenario, β_{time} is the coefficient for time window, $\beta_{\text{info}*\text{time}}$ is the interaction effects coefficient for information scenario and time window, $\gamma_{\text{participant}}$ is the random effects coefficient for participant-repeated measures, and ε is the normally distributed error term. Statistical analyses are performed using the *statsmodels* module in the Python programming language (StatsModels, 2019).

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

2.3 Results and Discussion

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

The LMM results for the freeway and arterial routes are illustrated in Figure 2.8 and Figure 2.9, respectively. Each figure illustrates a collection of heatmap-based visualization of the model coefficients for all EEG channels (hereafter referred to as *brain-maps*) grouped by experiment runs (row) and EEG bands (column). The brain-maps in the first row of each run (i.e., NI-t_1, NI-t_2 and NI-t_3) and the first column of each EEG band (i.e., CT-t_0, AT-t_0 and PI-t_0) represent the main effects of the time stages and the information scenarios, respectively, while the other brain-maps represent their interaction effects. The changes in band powers (i.e., the model coefficients) due to the main and interaction effects are depicted as heatmaps, with red indicating positive values (i.e., marginal increase in the band power due to the effect) and blue indicating negative values (i.e., marginal decrease in the band power due to the effect). The coefficients with statistical significance level of 99% and 95% are represented by solid circles and hollow circles, respectively, in the figures. The model intercepts denote the reference brain-maps (i.e., NI-t_0) and are not shown in the figures as their magnitudes are significantly higher than those of the effects.

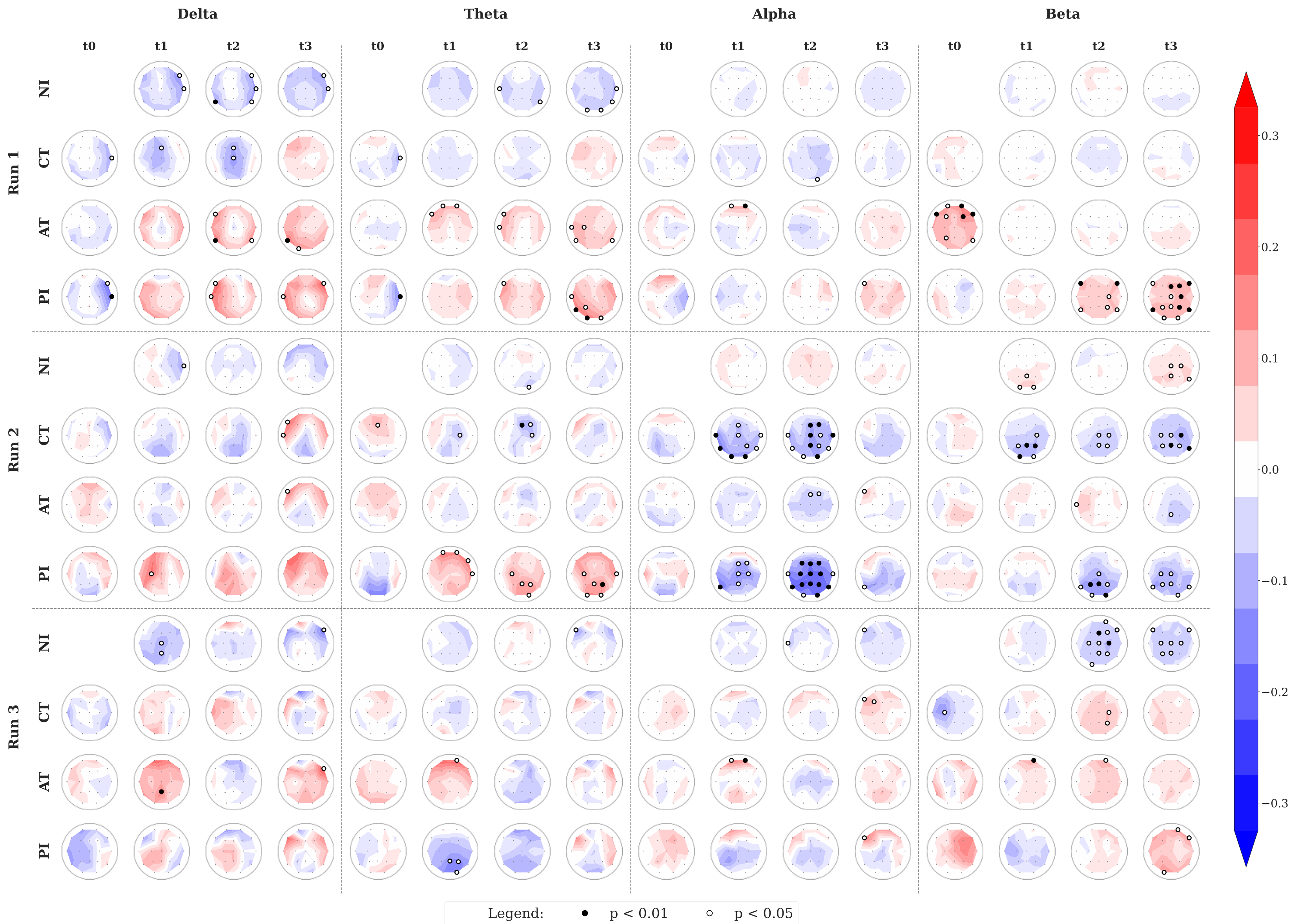

Figure 2.8 Linear mixed model results for the freeway route

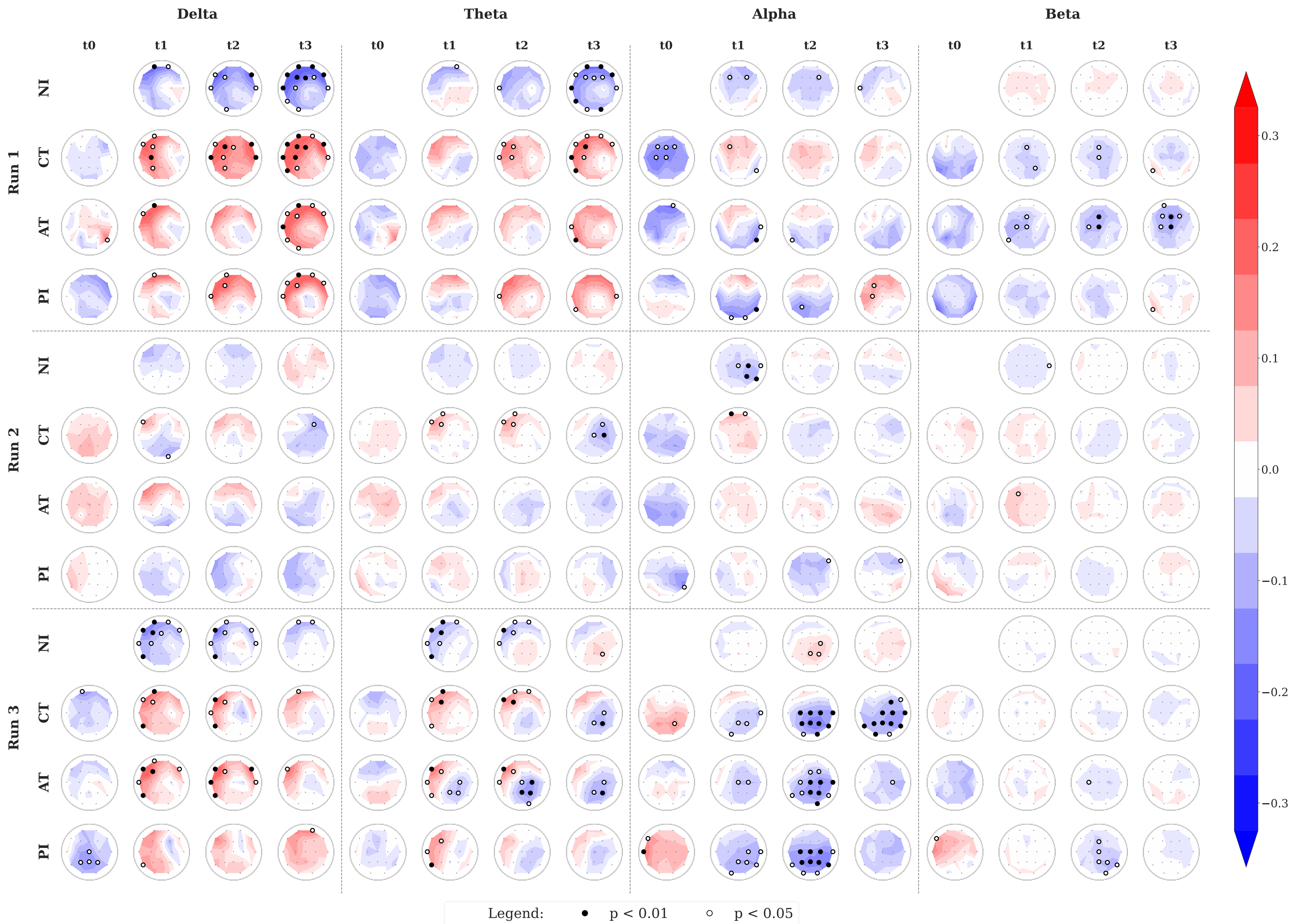

Figure 2.9 Linear mixed model results for the arterial route

2.3.1 Effects of driving environment complexity

In the first experiment run (run 1), as participants do not have prior experience with information provision, the differences in band powers in Figure 2.8 and Figure 2.9 under the NI scenario are likely caused by the systematic effects of the driving environment complexity. These differences are illustrated by the run 1 model coefficients of the NI scenario (i.e., NI-t_1, NI-t_2 and NI-t_3 brain-maps) for both freeway and arterial routes. As illustrated in Figure 2.8, there are little or no differences in the EEG band powers for the freeway route. The slightly lower delta and theta band powers, especially in the sensory regions of the brain (i.e., temporal and occipital), indicate systematic impacts of the driving environment in the vicinity of the information provision location. This reasoning is further supported by the significantly lower delta and theta band powers for the arterial route as illustrated in Figure 2.9, which has a more complex and dynamic driving environment than the freeway route. The steadily decreasing delta and theta band powers with time, mainly in the frontal and temporal regions of the brain, on the arterial route under NI are most likely caused by the diminishing task demand (i.e., attention to internal processing, memory retrieval, and memory processing) after drivers' interactions with the road objects providing trip-related information (for example, street name signs) upstream of the information provision location (i.e., during t_0). This is consistent with the study network as the first information provision location on the arterial route is immediately after an intersection comprising of several road objects (see Figure 2.1). These results indicate that the driving environment in the vicinity of the information provision location affects the EEG band powers.

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

2.3.2 Effects of information characteristics

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

2.3.3 Interaction effects of driving environment complexity and information characteristics

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

The slightly lower alpha band power in the temporal and occipital regions of the brain during the auditory information under AT and PI on the arterial route in run 1 compared to the mostly unchanged alpha band power under CT suggests that drivers exhibit higher alertness and sensory-intake to perceive and process more information units (AT and PI have twice the amount of information units as CT). Similarly, the lower beta band power under AT compared to CT on the arterial route in run 1 illustrates a higher level of driver distraction from the semantic task (i.e., perceiving and processing auditory information) due to more amount of information. However, these band powers are either slightly higher or mostly unchanged on the freeway route, indicating that the aforementioned cognitive effects of the information amount are exhibited primarily when driving in a complex driving environment. These findings illustrate an interesting tradeoff between information sufficiency and information amount (as they are typically positively correlated), where providing more units of auditory travel information and providing insufficient information in a complex driving environment increases driver distraction. Thus, information providers should avoid providing redundant information that will not add to the information sufficiency. Further, the underlying cause of distraction due to the higher information amount is primarily related to information perception, and it will likely vary with the modality of information (for example, auditory and visual). However, in case of insufficient information, distraction is related to memory retrieval and processing, which is independent of the information modality. Further research comparing different information modalities can aid in better understanding their roles.

The beta band power under PI is significantly higher after the first instance of auditory information (i.e., during t_2 and t_3) on the freeway route in run 1. By contrast, it is mostly unchanged on the arterial route. This suggests an increase in psychological stress and anxiety among drivers due to the recommended route switch to the arterial route, which is characterized by a higher travel time uncertainty. Therefore, while drivers expend lesser cognitive efforts to perceive and process the information on the freeway route, the recommendation to switch to the alternative route with higher travel time uncertainty due to downstream congestion on the current route results in a seemingly difficult route choice decision and induces stress and anxiety. The increased psychological stress and anxiety can adversely impact the consistency of drivers' route choice decision-making process. Consequently, it will reduce the reliability of traffic network flow predictions under real-time information provision in complex driving environments if it is not explicitly factored in route choice behavior models by traffic operators. Further, inadequate consideration of these psychological effects can negatively affect user experience with the information systems and reduce their trust in these systems.

2.3.4 Other effects

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

On the arterial route in run 2, the mostly unchanged delta and theta band powers under NI suggest reduced systematic effects of the driving environment, likely because of the reduced attention towards the road objects providing trip-related information before the information provision location. This is also supported by the slightly lower alpha band power in the parietal and temporal regions of the brain during t_1, which could manifest from the expectancy of real-time information and simple memory task to pinpoint the information provision location from recognizable landmarks (i.e., road signs and built environment in the simulator) on the arterial route. Similarly, on the freeway route in run 2, the higher beta band power in the parietal and occipital regions of the brain under NI during t_1 and t_3 suggests a possible increase in drivers' attention to external stimuli in anticipation of information and an increase in psychological stress and anxiety when the information is not received, respectively. On the arterial route in run 3, the delta and theta band powers under NI are lower (similar to run 1), but with reduced magnitude and an increasing trend over time. This could be because of the quicker recognition of road characteristics due to increased familiarity with the study network. These findings illustrate the learning (familiarity) effects of drivers with the driving environment and real-time information systems. It also illustrates the importance of providing real-time travel information consistently (by information providers) at locations where drivers expect to receive information, to avoid unwanted psychological stress and anxiety.

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

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

Table 2.2 Summary of the cognitive and psychological effects of driving environment complexity and information characteristics

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

Run 1	Arterial	CT	Information amount	Beta	Slightly lower	Higher level of driver distraction from a semantic task of perceiving and processing more information units in a complex environment	-	Driver distraction due to information perception
		AT			Lower			
Run 1	Freeway	PI	Information content	Beta	Significantly higher	-	Higher psychological stress and anxiety due to the recommended switch to a more complex route with higher travel time uncertainty	Adverse implications for modeling route choice behavior
	Arterial				Mostly unchanged			
Other effects								
Run 2	Arterial	NI	-	Delta and theta	Mostly unchanged	Reduced attention towards the road objects in a complex environment	-	-
Run 2	Arterial	NI	-	Alpha	Slightly lower	Expectancy of information and simple memory tasks to pinpoint information location in a complex environment	-	-
Run 2	Freeway	NI	-	Beta	Higher	Increase in attention to external stimuli in anticipation of information	Increase in psychological stress and anxiety due to not receiving information	Avoidable stress and anxiety by providing information at expected locations
Run 2	Freeway	PI	Information content	Theta	Higher	Higher task demand in the absence of descriptive information	-	-
		CT/AT			Lower or mostly unchanged			
Run 2	Freeway	CT/PI	Information sufficiency and content	Alpha	Significantly lower	Increase in simple memory tasks to recall missing travel time information on the alternative route	-	-
		AT			Slightly lower			

Run 2	Freeway	CT/PI	Information sufficiency and content	Beta	Lower	-	Lower psychological stress and anxiety due to receiving information about the current route	Reduced stress and anxiety to reaffirm premeditated decisions
		AT			Mostly unchanged			
Run 3	Arterial	NI	-	Delta and theta	Lower and increasing with time	Quicker recognition of road characteristics due to increased familiarity compared to run 1	-	-
Run 3	Arterial	CT/AT	-	Delta and theta	Higher and decreasing with time	Quicker memory retrieval and processing of the information compared to run 1	-	-
Run 3	Arterial	CT/AT	Information content	Delta and theta	Lower (in parietal region)	Reduced drowsiness due to receiving descriptive information	-	Descriptive information provision can help reduce driver drowsiness
		PI			Mostly unchanged (in parietal region)			
Run 3	Arterial	CT/AT/PI	Information provision	Alpha	Lower	Higher alertness, simple memory tasks, and sensory-intake to perceive and process information due to increasing familiarity	-	-

A summary of the cognitive and psychological main and interaction effects of the driving environment complexity and information characteristics, and their implications for different stakeholders, is presented in Table 2.2.

As discussed before, the second and third experiment runs are affected by the overlapping presence of learning effects with the equipment (i.e. driving simulator), study network, and information sources as well as driver fatigue and drowsiness, which limits the ability of the current experiment design to make concrete inferences on the cognitive and psychological effects of real-time information for these runs. More focused experiment designs are needed to analyze the impacts of learning, fatigue, and drowsiness on the cognitive and psychological effects of real-time information provision.

2.4 Concluding Comments

An understanding of traveler interactions with information provided in an increasingly information-rich vehicular environment is critical to the design of user-friendly in-vehicle environments as well as information design and delivery. In this context, this study evaluates the cognitive and psychological effects of real-time auditory travel information on drivers. EEG is used to measure drivers' brain electrical signals to estimate the information-induced cognitive and psychological effects in a network-level driving simulator environment in which drivers choose between two routes (arterial and freeway) with different driving environment complexity (in terms of route characteristics and macroscopic traffic conditions) to reach the destination.

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

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

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

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

3. HYBRID ROUTE CHOICE MODEL INCORPORATING LATENT COGNITIVE EFFECTS OF REAL-TIME TRAVEL INFORMATION USING PHYSIOLOGICAL DATA

3.1 Introduction

Drivers' route choices have direct impacts on the network traffic flow evolution. Therefore, a comprehensive understanding of route choice under real-time information provision is crucial for traffic operators and transportation planners to design and deploy effective traffic management strategies using Advanced Traveler Information Systems (ATIS) to alleviate traffic congestion. Several route choice behavior models have been proposed under real-time travel information available through ATIS (e.g., Abdel-Aty et al., 1997; Ben-Elia et al., 2013; Peeta & Yu, 2004). Typically, these route choice models incorporate factors such as route characteristics (e.g., travel time and its variability, and driving environment complexity), driver attributes (e.g., sociodemographic characteristics and inherent attitudes/beliefs), situational factors (e.g., downstream congestion and weather conditions), and real-time information characteristics (e.g., amount, source, and content). However, in the context of en route real-time information, most existing models are limited in their ability to factor latent cognitive (e.g., increased alertness and cognitive processing) effects of real-time information, and assume that the drivers are able to seamlessly perceive, process, and utilize travel information while performing an already cognition-heavy driving task.

Past studies suggest that interacting with information systems (not necessarily only ATIS) while driving increases the driver's cognitive workload and distraction, which can reduce the effectiveness of the disseminated information and have negative road safety implications, respectively (Birrell & Young, 2011; Jamson & Merat, 2005; Ranney et al., 2013). Recent advances in information and communication technologies have increased the complexity and diversity of real-time travel information available through multiple sources such as personal devices and public infrastructure. Real-time information available under the emerging connected transportation technologies will further exacerbate these concerns. Hence, there is an increasing critical need to consider human factors and cognitive aspects in route choice modeling under real-time travel information provision.

Previous studies related to real-time information provision have analyzed the impacts of information characteristics such as information quality (i.e., reliability and accuracy) (Ben-Elia et al., 2013; P. S.-T. Chen et al., 1999), content (Khattak et al., 1996; Peeta et al., 2000; Polydoropoulou et al., 1996), amount (Peeta et al., 2000), and source (Hato et al., 1999) on the driver route choice behavior. Existing route choice models have also incorporated the effects of route characteristics such as travel time variability (Abdel-Aty et al., 1997) and route complexity (Peeta & Yu, 2004, 2005), the effects of situational factors such as weather conditions, trip purpose (Yu & Peeta, 2011), and traffic congestion (L. Zhang & Levinson, 2008), and the effects of driver attributes such as age, gender, and other sociodemographic characteristics (Bekhor & Albert, 2014; Choocharukul, 2008). Other studies have illustrated the importance of factoring drivers' attitudes towards and experiences with real-time information systems in route choice models to improve the effectiveness of ATIS (Paz & Peeta, 2008, 2009a, 2009b, 2009c). Some of these include information acquisition and usage behavior (Hato et al., 1999), trust in information (Peeta & Yu, 2002), perceived usefulness of information (Choocharukul, 2008), and learning behavior and risk-seeking tendency under information provision (Ben-Elia et al., 2008). Some studies have also proposed route choice models based on well-defined behavioral theories (see Ben-Elia & Avineri, 2015 for a review), such as bounded rationality (Nakayama et al., 2001), prospect theory (Gao et al., 2010), and regret theory (Chorus, 2012). While existing route choice models have captured several aspects of driver behavior under information provision, primarily related to the roles of information, route, driver and some situational characteristics, they mostly do not factor the critical role of human capability in that they assume seamless perception and processing of the information provided. Thereby, they ignore the cognitive aspects of drivers' interactions with real-time information systems induced by information provision on their route choice decision-making process, which can adversely affect the reliability of network traffic flow predictions. This is a key limitation of the existing models as humans have limited cognitive resources that are divided across different tasks (Wickens, 2008) and driving is a multitasking activity that requires substantial cognitive efforts and attentional resources from the drivers. Thus, cognitive resources available to drivers to perceive, process, and utilize real-time information are greatly affected by the information characteristics as well as driving environment complexity, driver attributes, and situational factors. Further, the increasing prevalence and complexity of real-time information makes it even more critical to investigate the latent cognitive effects of information and analyze their impacts on drivers' route choice decisions.

Some studies have incorporated latent cognitive effects such as information acquisition intent, information processing capability, memory, and spatial ability in route choice models to consider the limitations of human cognition (Hato et al., 1999; Prato et al., 2012). However, they estimate these latent effects as a general human capability using subjective self-reported data from travel or web-based surveys and ignore the cognitive aspects of driving under different information characteristics, route characteristics, and situational factors. Song et al. (2017) addressed this gap by designing driving simulator experiments with a network-level setup and collecting subjective self-reported survey data to estimate the latent information-induced psychological effects, including cognitive burden, cognitive decisiveness, and emotional relief, and model their impacts on the revealed route choices. However, these studies rely on subjective self-reported data that can be limited by memory and reporting biases (e.g., transience and misattribution) (Schacter, 1999; van de Mortel, 2008), and do not directly measure the indicators of the latent cognitive effects of information. Further, there exists a potential for choice-supportive memory distortion (Mather et al., 2000), which occurs during the memory retrieval whereby people tend to attribute more positive features to the option that they chose. Song et al. (2017) avoid certain memory biases that get exacerbated as the time passes (e.g., lagged memory bias) by administering the survey immediately after the participant moves past a route choice decision point (that is, either switches or does not switch from the current route).

Recent advances in biosensing equipment (e.g., electroencephalogram (EEG)) and driver monitoring systems have enabled the evaluation of driver cognitive aspects using physiological indicators (e.g., brain electrical activity) that can be measured directly and non-intrusively. EEG data enables estimating a more detailed profile of drivers' cognitive state compared to other physiological indicators (e.g., heart rate and eye-tracking measures) by directly analyzing brain electrical activity patterns (e.g., EEG signal band powers) in different regions of the brain (Abhang et al., 2016b; Agrawal et al., 2020). In the driving context, previous studies have used EEG-based measures to assess driving fatigue (Morales et al., 2017), drowsiness (Brown et al., 2013), distraction (Sonnleitner et al., 2014), workload or stress (I. Solís-Marcos & Kircher, 2018), and driving behavior (Yang et al., 2018). In a previous study (Agrawal et al., 2020), we illustrated the efficacy of using EEG indicators (i.e., EEG band powers) to estimate the cognitive and psychological effects of real-time information and analyzed the impacts of information characteristics and route characteristics on the estimated effects. Here, we leverage insights from our previous study to estimate the latent information-induced cognitive effects using physiological (EEG) indicators, and incorporate them along with other explanatory variables that can be measured directly (i.e., route characteristics, information characteristics, driver attributes, and situational factors), in a hybrid route choice modeling framework to predict route choice decisions under real-time information.

To develop robust route choice models under real-time information provision, it is critical to not only analyze the effects of explanatory factors that can be measured directly, but also to adequately incorporate the cognitive effects of information that affects the route choice decision-making process. In this context, this study estimates the latent information-induced cognitive effects using drivers' EEG data which is collected non-intrusively in driving simulator experiments, and incorporates their effects on drivers' route choices in a hybrid route choice modeling framework. To the best of our knowledge, this is the first study to model route choice behavior under real-time information provision using drivers' physiological indicators. In addition, we analyze the impacts of explanatory factors, including route characteristics (i.e., route complexity), information characteristics (i.e., amount, content, and source), driver attributes (i.e., sociodemographic characteristics), and situational factors (i.e., downstream congestion), on the latent effects, as well as their overall impacts on route choice decisions. The model is calibrated using data collected from driving simulator experiments with a network-level setup that features two routes with different characteristics (in terms of travel time and driving environment complexity) and dynamic ambient traffic. The proposed model enhances the understanding of drivers' route choice decision-making process by incorporating the cognitive effects and will aid traffic operators to design real-time information dissemination strategies for managing traffic networks more effectively. It also provides insights for information service providers and auto manufacturers to design information and its delivery systems from the perspective of driver cognition, and thereby, potentially enhances road safety and user experience.

The study contributions are as follows. First, it circumvents the biases associated with subjective self-reported data by estimating the latent cognitive effects of information using objective physiological indicators (i.e., EEG indicators) that are measured directly during and immediately after the information provision and before implementing the route choice decision in driving simulator experiments. By doing so, we capture the impacts of cognitive effects arising from interactions with real-time information, such as cognitive processing (i.e., thinking, remembering, and problem-solving), level of concentration and arousal, and attention towards the information and the driving environment, which have not been considered in the existing studies. Second, we propose a hybrid route choice model that analyzes the effects of explanatory factors on the latent cognitive effects (e.g., cognitive effort and attentional resources) and model their combined impacts on drivers' route choices. This allows for a more robust analysis of the direct and indirect (i.e., through latent cognitive effects) effects of the explanatory factors on drivers' route choice behavior. Third, we use a network-level setup featuring routes with different driving environment complexity and dynamic ambient traffic in driving simulator experiments. The network-level setup in a driving simulator environment creates a realistic route choice decision-making context for the participants, where their route choices have considerable impacts on their travel times and the disseminated real-time travel information can help them to potentially reduce their travel times. It also enables us to simultaneously elicit the latent cognitive effects arising from the tasks of driving and interacting with information. This is important as allocating limited cognitive resources to different tasks can have significant impacts on drivers' information perception, processing, and utilization that subsequently affect route choice decisions. Fourth, to further extract behavioral and attitudinal realism from the participants, we implement novel mechanisms such as providing participants with a driving objective (i.e., morning commute trip) to elicit intent to reach the destination on time, and compensating them for their participation using a point-based reward system (see section 3.3.3 for more details) that tracks their intent to complete the trip on time while executing safe driving actions.

The remainder of the paper is organized as follows. Section 3.2 presents the conceptual hybrid route choice modeling framework. Section 3.3 outlines the driving simulator experiment design, data collection procedures, and data preprocessing methods. Section 3.4 discusses the model estimation results. Section 3.5 summarizes the study findings, and concludes the paper by providing some future research directions.

3.2 Conceptual hybrid route choice model

This study proposes a hybrid route choice model to incorporate the latent cognitive effects of real-time travel information along with several explanatory variables that can be measured directly, including route characteristics, driver attributes, situational factors, and real-time information characteristics. Unlike existing route choice models that heavily rely on subjective survey-based measures, we use drivers' physiological data (i.e., EEG) as indicators of their underlying latent cognitive processes during route choice decision-making under real-time information provision.

This study models information-induced cognitive effects as latent variables. A latent variable is a hypothetical construct that is inferred from the common variance among the observed indicator variable(s) (Kenny, 1979). We propose a Multiple Indicators Multiple Causes (MIMIC) model (Bollen, 1989), a variant of a Structural Equation Model (SEM), to simultaneously estimate latent variables using observed physiological indicators and predict them using observed explanatory variables. We define the driver's route choice decision as a binary variable ($\mathcal{R}$) indicating a switch from the current route; that is, $\mathcal{R}$ is equal to 1 if the driver switches from the current route and 0 if the driver stays on the current route. It is analyzed using a random utility discrete choice model with a probit link function within the MIMIC framework; a probit link function transforms probabilities to the standard normal variable ($\mathcal{N}(0,1)$) using the inverse of the cumulative distribution function of the standard normal distribution. Figure 3.1 presents a conceptual framework of the proposed hybrid route choice model.

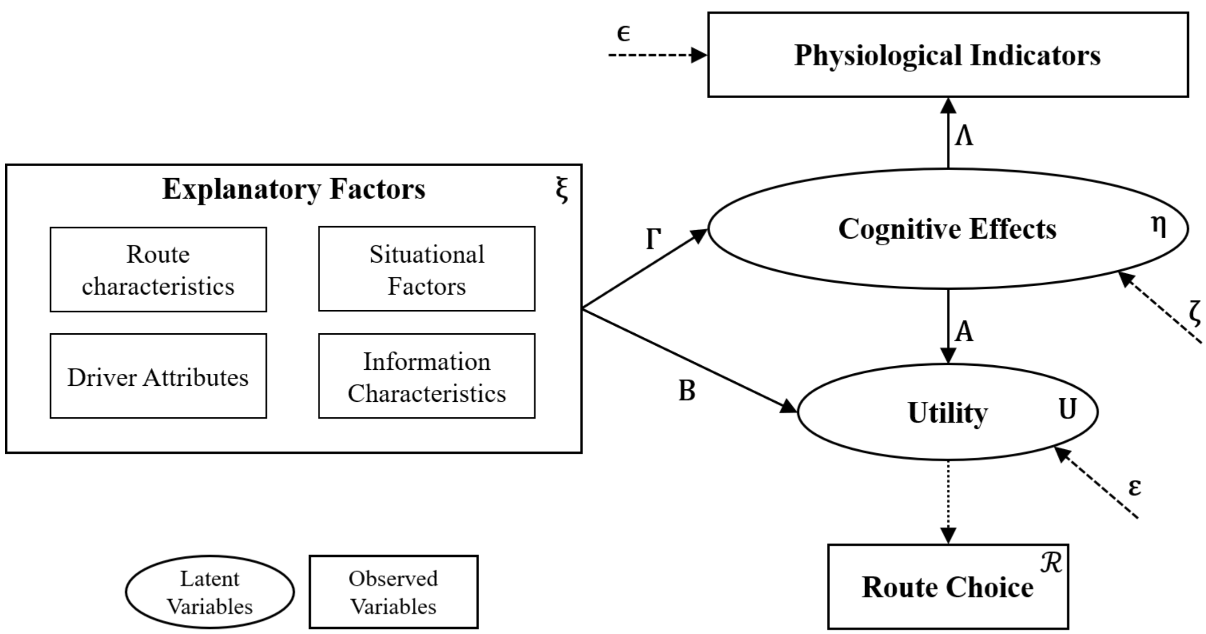

Figure 3.1 Conceptual hybrid route choice model with physiological indicators

A SEM model consists of two parts: a measurement model that specifies the measurement relationships between the observed indicator variables and the latent variables, and a structural model that specifies structural relationships between the explanatory variables, the latent variables, and the latent random utility. The measurement model is given by Eq. (3.1).

$$\mathbf{y} = \mathbf{\Lambda\eta} + \boldsymbol{\epsilon}; \quad \boldsymbol{\epsilon} \sim N(0, \mathbf{\Sigma}_{\boldsymbol{\epsilon}}) \tag{3.1}$$

In Eq. (3.1), $\mathbf{y}$ is a vector (for all individuals) of indicator variables, $\boldsymbol{\eta}$ is a vector of latent variables, $\mathbf{\Lambda}$ is a coefficient matrix of factor loadings (i.e., coefficients relating latent variables and indicator variables) for $\mathbf{y}$ and $\boldsymbol{\eta}$. The residuals ($\boldsymbol{\epsilon}$) are assumed to be multivariate normally-distributed independent errors with mean of zero.

The structural model for the latent variables is given by Eq. (3.2), and for the random utilities is given by Eq. (3.3).

$$\boldsymbol{\eta} = \mathbf{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta}; \quad \boldsymbol{\zeta} \sim N\left(0, \mathbf{\Sigma}_{\zeta}\right) \tag{3.2}$$

$$\mathbf{U} = \mathbf{A}\boldsymbol{\eta} + \mathbf{B}\boldsymbol{\xi} + \boldsymbol{\varepsilon}; \quad \boldsymbol{\varepsilon} \sim N(0, \mathbf{\Sigma}_{\boldsymbol{\varepsilon}}) \tag{3.3}$$

$$\Pr(\mathcal{R} = 1|\mathbf{U}) = \Phi(\mathbf{U}) \tag{3.4}$$

In Eq. (3.2), $\boldsymbol{\xi}$ is a vector of explanatory variables, $\mathbf{\Gamma}$ is a matrix of structural coefficients relating $\boldsymbol{\xi}$ and $\boldsymbol{\eta}$, and $\boldsymbol{\zeta}$ is a vector of multivariable normally-distributed independent errors with mean of zero. In Eq. (3.3), $\mathbf{U}$ is a vector of latent random utilities, and $\mathbf{A}$ and $\mathbf{B}$ are matrices of structural coefficients relating $\mathbf{U}$ with $\boldsymbol{\eta}$ and $\boldsymbol{\xi}$, respectively. The residuals ($\boldsymbol{\varepsilon}$) are assumed to be identical and independently normally distributed with mean of zero. Eq. (3.4) represents the probability of route switch (i.e., $\mathcal{R} = 1$) for a given utility value as the standard normal cumulative distribution function Φ.

3.3 Methodology

3.3.1 Apparatus

3.3.1.1 Driving simulator

A medium-fidelity fixed-base driving simulator (AVSimulation, 2020) was used to collect data for this research (see Figure 3.2). The simulator features a full-scale driving cockpit with automatic transmission and a force feedback-enabled steering wheel. The driving environment is projected on three LCD screens providing a field-of-view of approximately 120 degrees. Side-view mirrors, rear-view mirror, and speedometer are presented on the screens. Additionally, departure time, estimated time to arrival, and elapsed time are shown on the top-left corner of the center screen.

Figure 3.2 Driving simulator

A network-level setup that replicates the northern loop in Indianapolis, Indiana was created using the SCANeRStudio® 1.4 software (see Figure 3.3). Drivers (study participants) could choose between two routes (freeway and arterial) to reach their destination, as illustrated in Figure 3.3. The two routes differed in terms of driving environment complexity (e.g., speed limit, number of intersections/interchanges, density of road objects) and traffic interactions. The freeway route was longer compared to the arterial route (16 miles vs. 11 miles) but took lesser travel time, on average, to reach the destination (21 minutes vs. 25 minutes) under normal traffic conditions. Further, the arterial route was characterized by a larger travel time uncertainty due to a more complex driving environment compared to the freeway route. As shown in the figure, drivers could switch their route at two route choice locations during the trip. Real-time travel information could be provided before each route choice location; personalized information through personal device(s) and generic information through variable message sign. The information was delivered at least a minute before the route choice location to provide adequate time for drivers to perceive and process the information. Additionally, to create a realistic driving environment, dynamic and responsive ambient traffic was generated by integrating a microscopic traffic simulator (AIMSUN 6.2; Transport Simulation Systems, 2017) with the driving simulator in real-time. The generated traffic conditions were consistent with the information and traffic congestion scenarios designed in the study experiments (see section 3.3.2 for details).

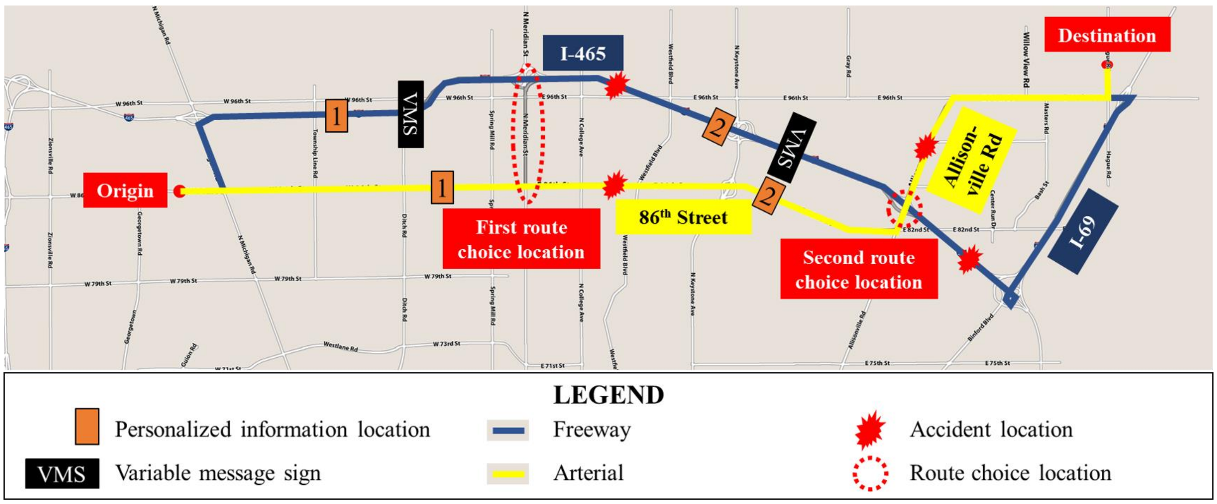

Figure 3.3 Experiment setup

3.3.1.2 Electroencephalogram (EEG)

A B-Alert X24 electroencephalogram (EEG) system was used to record participants' brain electrical signals with a sampling rate of 256 Hz during the experiment runs (Advanced Brain Monitoring, 2017). Nineteen EEG electrodes (hereafter referred to as EEG channels) were placed according to the International 10-20 system (Klem et al., 1999) as shown in Figure 3.4. Each EEG channel corresponds to a specific brain region or lobe as illustrated in Table 3.1.

Raw EEG signals were decontaminated using the B-Alert software that removed the following artifacts associated with low- and high-frequency noise: electromyogram (muscle movements), eye blinks, excursions, amplifier saturations, and spikes (B-Alert, 2009). Power spectral density of EEG signals for 1-second epochs was computed using fast Fourier transformation with a 50% overlapping window to smoothen the data. Then, the band powers for delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz), and beta (13-30 Hz) bands were computed by averaging power spectral density of the EEG signal within their corresponding band frequencies. A comprehensive description of information-induced cognitive and psychological effects associated with different band powers in different regions of the brain is provided in Agrawal et al. (2020).

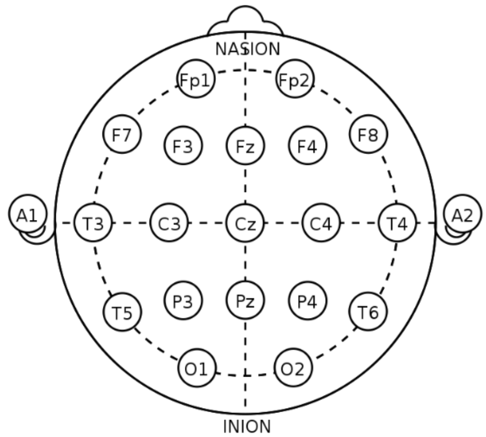

Figure 3.4 EEG electrode placement (source: Wikipedia, 2019)

Table 3.1 Brain lobes corresponding to EEG channels

Brain regions	**EEG channels**
Frontal lobe (F)	Fp1, Fp2, F7, F3, Fz, F4, F8
Centroparietal lobe (P)	P3, Pz, P4, C3, Cz, C4
Temporal lobe (T)	T3, T4, T5, T6
Occipital lobe (O)	O1, O2
Mastoids (EEG reference)	A1, A2

3.3.1.3 Global Positioning System (GPS)

A tablet-based GPS was developed to show the ego vehicle's current position and direction on a zoomed-in view of the road network. Similar to most commercially available GPS and navigation mobile applications, the vehicle position was pinned at the center of the screen while the road map moved in the background. All roads on which the participants were allowed to drive on were highlighted in grey to provide clarity on the routes used in the experiments; thereby, it implied a basic level of familiarity with the road network. The GPS was placed on the simulator dashboard as shown in Figure 3.2.

3.3.2 Experiment design

Two traffic congestion scenarios (with and without congestion on the current route) were created to analyze the effects of downstream congestion on drivers' route choices. Traffic congestion was simulated to reduce the current route's capacity by creating a road accident immediately after the route choice location (see Figure 3.3), resulting in blocked lane(s) (one out of two lanes on the arterial route and two out of five lanes on the freeway route).

Two sources of real-time travel information provision are used in this study: personal device and public infrastructure. Personalized travel information was provided in the auditory format through two multimedia speakers that were positioned on each side of the driving cockpit below the screens. Public travel information was provided via on-road VMSs in the simulated environment on the freeway route. Hence, real-time travel information could be provided before each route choice location. However, this study analyzed drivers' route choice decisions for the first route choice location only to avoid the interaction effects associated with multiple real-time information provisions in a single trip.

Four real-time information scenarios were created to analyze the impacts of real-time information characteristics on route choice behavior. They include: (i) no information (NI), (ii) travel time on the current route (CT), (iii) travel times on the current and alternative routes (AT), and (iv) prescriptive information recommending the alternative route due to downstream congestion (PI). Under CT and AT, travel time to the destination was provided on the personal device while travel time to a specific landmark (i.e., I-69 and Allisonville road) was provided on the VMS. PI was available only on the personal device. From an information content perspective, the information provided under CT and AT can be characterized as descriptive information, as opposed to the prescriptive information under PI. From an information amount perspective, AT and PI are characterized as high amount of information (two units of information) and CT as low amount of information (one unit of information) (Dudek, 2004). From an information sufficiency perspective, AT and PI are characterized as sufficient information (travel information for both routes) and CT as insufficient information (travel information for the current route only). PI was available only in scenarios with traffic congestion. Information scenarios for the two sources were independent of each other. However, the following constraint was added to reduce the combinations of experimental scenarios: if one source provided CT, the other source provided either NI or CT. Further, the maximum number of road accidents in each experiment run was limited to one. More details on information and traffic congestion scenarios for each route and information source can be found in Appendix A. In this study, the information was designed to promote a route switch from the current route by either making the alternative route more attractive in terms of the travel time or by recommending it due to downstream congestion on the current route (see Appendix A).

3.3.3 Experiment procedure

Before arriving at the lab for the driving simulator experiments, participants completed an online questionnaire designed to gather information about their attitudes toward and experiences with real-time travel information, and sociodemographic details. During the lab visit, participants signed an informed consent form and were introduced to the complete experiment procedure. Then, they completed a practice run designed to acclimatize them with the simulator and create a basic level of familiarity with the road network and information sources while checking for simulator sickness. Those showing signs of motion sickness at this stage were not allowed to proceed further. In the practice run, participants started driving from the intersection upstream of the first information provision location on the arterial route to the second route choice location while switching to the freeway route at the first route choice location. Participants were also informed about the distance (i.e., 16 miles for the freeway route and 11 miles for the arterial route) and expected travel time (i.e., 21 minutes for the freeway route and 25 minutes for the arterial route) to reach the destination under normal traffic conditions for each route. Fast-forwarded driving videos of both routes with pauses at critical intersections and signage were shown to the participants to enhance familiarity with the study network and information sources. Next, they were equipped with EEG and were asked to complete an EEG baseline test in the B-Alert software (B-Alert, 2009) in a quiet room. Following this, they were equipped with an eye tracking device. Then, they were asked to complete another simulated run following simple on-screen instructions (e.g., "stay in the middle lane") that was designed to verify EEG data acquisition. After this run, participants filled a survey indicating their familiarity with the study network and their preferred route. Then, each participant was asked to execute three experiment runs from the origin to the destination using randomly-assigned information and traffic congestion scenarios. They were instructed to drive as if they are commuting to work. To promote a realistic driving and decision-making behavior, participants were compensated up to $60 based on a point-based reward system that tracked their intent to complete the trip within the assigned 25-minute time limit while complying with traffic rules and driving safely. However, the participants were neither able to track the reward system nor informed about the actual points gained or lost with time until the end of the three runs. After each run, they completed a post-run self-reported survey related to information perception, factors considered in route choice decision, travel satisfaction, and preferred route for the next run.

3.3.4 Data preprocessing

Regional averages of the band powers of the EEG signal for each brain region were computed by averaging the band powers in corresponding EEG channels (see Table 3.1). This helps to reduce the number of variables without losing much inferential power as brain functionality is often discussed at the region level. The band powers were further aggregated by averaging 1-second epoch band powers for three time windows corresponding to the first route choice location: (i) before the information provision (t_0), (ii) during and immediately after the information provision (t_1), and (iii) before the route choice location (t_2). Time window t_0 was used as baseline for analyzing the band powers to mitigate the effects of heterogeneity in drivers' EEG data as well as systematic differences between the two routes due to road characteristics (e.g., road curvature and speed limit) and macro-level traffic conditions. It is defined as the 10-second time period before the personalized information location (see Figure 3.3 for locations). Time window t_1 represents the information perception and processing phase (hereafter referred to as information phase). The size of this window depends on the type of information provided in a particular run. If only personalized information was provided, t_1 is the time period between the start of the auditory information and 10 seconds after the end of that information provision. If the information is provided only via VMS, t_1 is the time period between 5 seconds before crossing the VMS (when the VMS message becomes legible) and 10 seconds after crossing it. If both information sources are present, then t_1 is considered as the combination of both of these time periods. Note that in the case of no personalized information, the size of t_1 is zero. Time window t_2 represents the route choice implementation phase and is defined as 10-second time period before reaching the intersection (on the arterial route) or exit (on the freeway route) for the first route choice location, at which point the routing decision would be revealed. Then, the logarithmic band powers were computed to normalize the distribution. The logarithmic band powers in zero-sized t_1 were set to zero. Finally, the logarithmic band power in the reference time window t_0 is subtracted from non-zero logarithmic band powers in t_1 and t_2 to obtain EEG variables for the model.

To summarize, 32 EEG variables were computed and considered for the hybrid model. EEG variables during the information phase and choice implementation phase are denoted as $\mathcal{I}_r^b$ and $\mathcal{C}_r^b$, respectively, where r is the brain region, namely, frontal (F), centroparietal (P), temporal (T), and occipital (O), and b is the EEG band, namely, delta (δ), theta (θ), alpha (α), and beta (β).

3.3.5 Participants

Participants were recruited from the Greater Lafayette community in Indiana, USA, through advertisements in the Purdue University's weekly email newsletter, paper fliers at community events, and word of mouth. Participant eligibility criteria included: (i) being 18 years of age or older, (ii) having a valid driver's license, (iii) having no predisposition to motion sickness, (iv) not self-reporting mental or physical impairments, and (v) not wearing any corrective glasses (as it hinders the eye tracking device). In addition, they were asked not to consume any medication or caffeine for at least 8 hours prior to the experiment as certain medications and caffeine ingestion may affect EEG patterns (Blume, 2006; Pritchard et al., 1995) and, thereby, deteriorate EEG data quality. The experiment protocol was approved by the Purdue University's Institutional Review Board (protocol # 1304013546). In total, 125 people participated in this study, and 95 of them completed all three runs with valid EEG data within the time windows defined in the previous section. Figure 3.5 shows the age and gender distribution of these participants. Figure 3.6 illustrates the information scenario distribution grouped by the traveled route for all experiment runs. Participants were compensated (with a maximum of $60) based on the point-based reward system discussed in section 3.3.3.

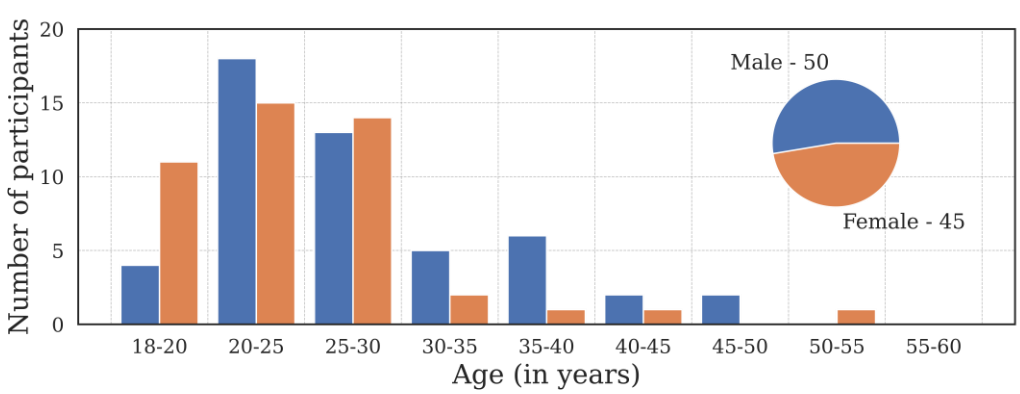

Figure 3.5 Age and gender distribution of the participants

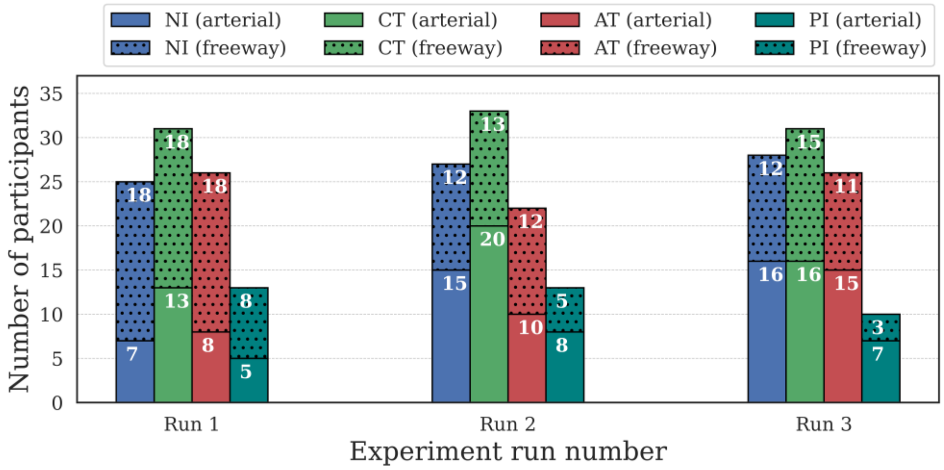

Figure 3.6 Information scenario distribution by route and experiment run

3.4 Model estimation results

To verify that EEG variables can be used as indicators in the measurement model (factor analysis), we performed Bartlett's Test of Sphericity for each phase (i.e., information and implementation) to check for the presence of correlations among EEG variables (Bartlett, 1937). Since the null hypothesis of this test is that the correlation matrix is an identity matrix, we want to reject the hypothesis. Bartlett's K-squared test statistics for the EEG variables during the information phase and choice implementation phase were 597.6 and 706.8, respectively, with 15 degrees of freedom and a p-value lower than 0.001 for both, indicating that the data is appropriate for the measurement model.

Since EEG band power in each frequency band is associated with certain cognitive functions (Abhang et al., 2016b), we define eight latent variables based on the four EEG bands for each of the two time windows (i.e., information phase and route choice implementation phase), with all the corresponding brain regions (see Table 3.1) as indicators. To identify the significant latent variables, we estimated a simplified hybrid route choice model with all latent variables and no explanatory variables using the lavaan package (Rosseel, 2012) implemented in R 4.0.0 (R Core Team, 2020). Two latent variables were found to be statistically significant ($p < 0.1$): the variable estimated using the beta band powers during the information phase ($\mathcal{I}^{\beta}$) and the variable estimated using the alpha band powers during the choice implementation phase ($\mathcal{C}^{\alpha}$).

Past literature has associated higher beta band powers with increased psychological stress (i.e., emotional strain and pressure) (Alonso et al., 2015) and higher cognitive effort, including concentration and increased arousal (Morales et al., 2017; Okogbaa et al., 1994), increase in cognitive processing (Ray & Cole, 1985), decision-making process (C.-T. Lin et al., 2018), and focused external attention (Abhang et al., 2016b). In our previous work (Agrawal et al., 2020), we reported an increase in beta band powers with an increase in psychological stress caused by a difficult route choice decision. Therefore, we postulate that the latent variable $\mathcal{J}^{\beta}$ represents the amount of cognitive effort drivers exert on processing real-time information as well as the psychological stress caused by it. Thus, we refer to $\mathcal{J}^{\beta}$ as the latent variable indicating cognitive effort under information provision.

Several studies have linked a decrease in the alpha band powers with an increase in alertness and attention towards external environment (Aftanas & Golocheikine, 2001; Okogbaa et al., 1994; Ray & Cole, 1985), and cognitive processing and expectancy (Aftanas & Golocheikine, 2001). Foxe et al. (1998) also associated lower parietal and occipital alpha band power with preparedness for incoming visual stimuli. In the context of real-time information, Agrawal et al. (2020) found that higher alertness to perceive and process more amount of information manifests as a decrease in the alpha band powers. Therefore, we postulate that $\mathcal{C}^{\alpha}$ represents the change in drivers' level of alertness and attention towards road environment, including the tendency to seek relevant visual cues, such as road signs and exits, during the choice implementation phase. Thus, we refer to $\mathcal{C}^{\alpha}$ as a latent variable indicating cognitive inattention before route choice implementation.

Next, we estimated the hybrid route choice model, as illustrated in Figure 3.7, using the latent variables and explanatory variables. Explanatory variables that were not found to be statistically significant ($p > 0.1$) were not included in the final model (see Appendix B for a list of all tested variables that were found to be statistically non-significant). The descriptions of the explanatory variables used in the final model are presented in Table 3.2.

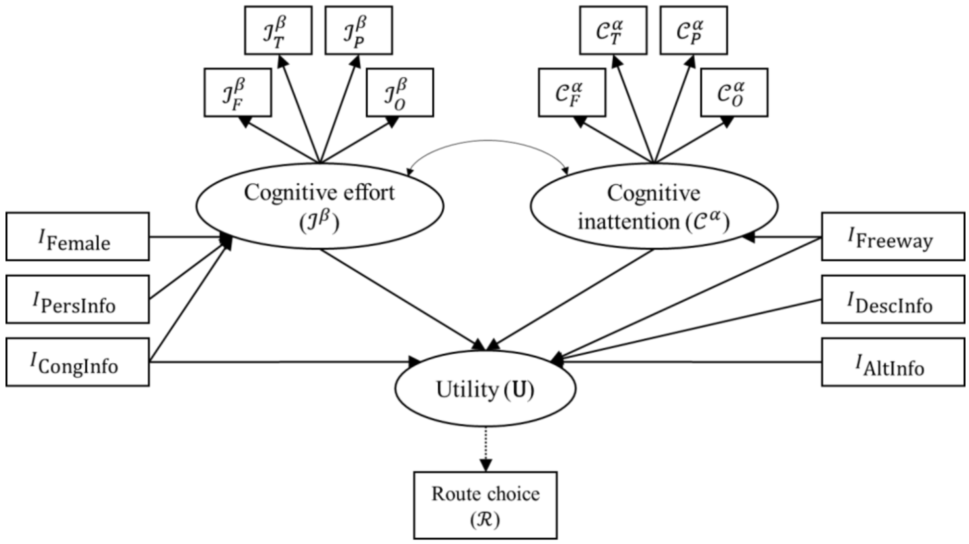

Figure 3.7 Estimated hybrid route choice model structure

Table 3.2 Variable description

Variable	Description
$\mathcal{R}$	Indicator for route change (1: switch from the current route; 0: otherwise)
U	Random utility (probit)
$\mathcal{J}^\beta$	Latent variable for cognitive effort (estimated using the beta band powers)
$\mathcal{C}^\alpha$	Latent variable for cognitive inattention (estimated using the alpha band powers)
I_{Female}	Female indicator (1 if female; 0 otherwise)
I_{PersInfo}	Indicator for personalized information (1 if personalized information is provided; 0 otherwise)
I_{CongInfo}	Indicator for traffic congestion information (1 if information is provided and there is congestion downstream; 0 otherwise)
I_{Freeway}	Freeway route indicator (1 if the current route is the freeway route; 0 otherwise)
I_{DescInfo}	Indicator for descriptive information (1 if CT or AT information is provided; 0 otherwise)
I_{AltInfo}	Indicator for alternative route information (1 if AT or PI information is provided; 0 otherwise); this variable also represents high amount of information or sufficient information

Model fit is assessed using: (i) Chi-square (χ^2) statistic which tests the null hypothesis that predicted and observed values are equal (p-value > 0.05 indicates a good model fit), (ii) Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) which measure incremental model fit

(CFI/TLI > 0.95 indicates a good model fit), and (iii) root mean square error of approximation (RMSEA) which is an absolute measure of fit. Kenny (1979) suggests that a p-value (χ^2) greater than 0.05, CFI/TLI greater than 0.95, and RMSEA less than 0.05 indicate a good model fit. The model fit measures for the estimated hybrid model, as presented in Table 3.3, indicate a good model fit.

Table 3.3 Hybrid route choice model fit measures

Fit measure	**Estimate [1]**	**p-value**
χ^2 (estimated model)	85.961	0.109
df (estimated model)	71	
χ^2 (null model)	983.521	0.000
df (null model)	36	
CFI	0.984	
TLI	0.992	
RMSEA	0.027	

[1] robust measure obtained using the WLSMV estimator in the lavaan package

Table 3.4 Measurement model estimation results

Latent Factor	$\mathcal{J}^{\beta}$		$\mathcal{C}^{\alpha}$	
Indicator Variable	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
$\mathcal{J}_F^{\beta}$	1.000	-	-	-
$\mathcal{J}_T^{\beta}$	1.485***	0.072	-	-
$\mathcal{J}_P^{\beta}$	1.513***	0.070	-	-
$\mathcal{J}_O^{\beta}$	1.459***	0.075	-	-
$\mathcal{C}_F^{\alpha}$	-	-	1.000	-
$\mathcal{C}_T^{\alpha}$	-	-	1.678***	0.165
$\mathcal{C}_P^{\alpha}$	-	-	1.517***	0.131
$\mathcal{C}_O^{\alpha}$	-	-	1.396***	0.124

*** p < 0.01   ** p < 0.05   * p < 0.10

The measurement model results, as illustrated in Table 3.4, indicate that the EEG variables for the beta band during the information phase in all regions (i.e., $\mathcal{J}_F^{\beta}$, $\mathcal{J}_T^{\beta}$, $\mathcal{J}_P^{\beta}$, and $\mathcal{J}_O^{\beta}$) have statistically significant ($p < 0.01$) factor loadings on $\mathcal{J}^{\beta}$. Similarly, the EEG variables for the alpha band during the choice implementation phase in all regions (i.e., $\mathcal{C}_F^{\alpha}$, $\mathcal{C}_T^{\alpha}$, $\mathcal{C}_P^{\alpha}$, and $\mathcal{C}_O^{\alpha}$) have statistically significant (p < 0.01) factor loadings on $\mathcal{C}^{\alpha}$. It should be noted that the contribution (i.e., factor loadings) of the frontal region, which is primarily related to task planning and memory (Chayer & Freedman, 2001), is lesser than those of the other regions for both latent variables. The estimated model covariance (double-headed curved arrow in Figure 3.7) between cognitive effort ($\mathcal{J}^{\beta}$) and cognitive inattention ($\mathcal{C}^{\alpha}$) is small (0.001) but statistically significant (p < 0.001). Other variances and covariances of the model variables are presented in Appendix B.

Table 3.5 presents the estimated coefficients of the structural model. It also presents the marginal effects of the latent variables and the explanatory variables on the probability of route switch. For continuous variables, the marginal effects on the probability of route switch are calculated by computing the change in probability when their mean is increased by a fixed amount of 0.01 while keeping all other variables at their mean values. The magnitude of the fixed amount of increase (0.01) is chosen based on the magnitude of the values of continuous latent variables to reasonably scale the marginal effects. For indicator variables, the marginal effects are calculated by changing the variable value from 0 to 1 (Kleiber & Zeileis, 2008).

Table 3.5 Structural model estimation results

Variable	$\boldsymbol{\mathcal{J}^{\beta}}$		$\boldsymbol{\mathcal{C}^{\alpha}}$		**U**		
	Estimate	**Std. Error**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**	**Marginal Effects (%)**
$\mathcal{J}^{\beta}$	-	-	-	-	4.951***	1.714	1.779
$\mathcal{C}^{\alpha}$	-	-	-	-	-2.087*	1.205	-0.762
I_{Female}	0.013*	0.007	-	-	-	-	-
I_{PersInfo}	-0.033**	0.015	-	-	-	-	-
I_{CongInfo}	0.016*	0.008	-	-	0.934***	0.211	31.253
I_{Freeway}	-	-	-0.024**	0.012	-1.302***	0.194	-44.553
I_{DescInfo}	-	-	-	-	0.855***	0.305	31.214
I_{AltInfo}	-	-	-	-	0.408*	0.226	14.582
Threshold for probit link: $\Pr(\mathcal{R} = 1 \mid \mathbf{U})$					0.628**	0.255	-

*** p < 0.01 ** p < 0.05 * p < 0.10

The following inferences can be made from the structural model estimation results for the latent variables in Table 3.5. First, the negative coefficient of I_{PersInfo} on latent cognitive effort variable suggests that drivers spend less cognitive effort to process, not necessarily perceive, auditory personalized information. Second, the positive coefficient of I_{CongInfo} indicates that drivers spend more effort to process and utilize congestion information, and that unfavorable information content can cause additional psychological stress. Third, the positive coefficient of I_{Female} indicates that female drivers either exert more cognitive effort to process and utilize real-time information, get more stressed under information provision, or both. Further, we tested the effects of driver's age and its covariate, driving experience, that may affect driver cognition and the route choice decision-making process (Song et al., 2017). However, we did not find their significant effects in the model, most likely because our study sample is skewed towards younger adults, and thus, the study participants exhibit similar cognitive abilities. Fourth, the negative coefficient of the freeway route indicator (I_{Freeway}) on the latent cognitive inattention variable suggests that drivers spend more attentional resources (i.e., lower value of C^{α}) to seek spatial information (i.e., road signs and exit) on the environment on the freeway route compared to the arterial route.

The structural model estimation results for the random utility illustrate the following impacts of route characteristics, information characteristics, and situational factors on the probability of route switch. First, drivers are more likely to switch their route if they receive information indicating downstream congestion on the current route. Second, drivers are less likely to switch from the freeway route to the arterial route. This may be because drivers perceive the freeway route to be more reliable in terms of travel time compared to the arterial route, due to its simpler road environment, especially when they do not have inadequate familiarity with and information about the network from their past experiences (Ben-Elia et al., 2013). Third, drivers are more likely to switch their route when provided with descriptive travel time information. This is in line with previous research indicating that drivers prefer quantitative information en route, especially about traffic delays (Polydoropoulou et al., 1996). Fourth, drivers are more likely to switch their route when they have sufficient information about the traffic situation, either in terms of route recommendation (PI) or travel times on both the current and alternative routes (AT). In addition, the marginal effects show that although drivers are considerably less likely to switch away from the freeway route, the overall information design (amount, sufficiency, and content), especially under traffic congestion, has significant impacts on their routing decisions. We also tested driver attributes such as income and education that capture the effects of heterogeneity in value of time on route choice behavior (Peeta et al., 2000). However, we did not find them to be significant in our model, most likely because we provided the same driving objective (i.e., morning commute) to the study participants and did not vary the trip purpose, which could have suppressed the effects of these attributes.

Further, the structural model estimation results also illustrate the following impacts of the latent cognitive effects of information on the route choice behavior. First, the positive coefficient of cognitive effort during the information phase ($\mathcal{J}^{\beta}$) indicates that drivers who are more diligent to process and utilize the information are more likely to switch route. This behavior is supported by the experiment design as the real-time information was designed to promote a route switch. However, it should be noted that a reversed causality is possible as well, that is, drivers who are interested in switching their route before receiving information expend more cognitive effort for processing and utilizing the information. Second, the negative coefficient of cognitive inattention ($\mathcal{C}^{\alpha}$) during the choice implementation phase implies that drivers who are less attentive towards the road environment (i.e., a higher value of $\mathcal{C}^{\alpha}$) are less likely to switch from the current route. This is reasonable as drivers who decide to switch route need to be more attentive to the road signs and intersections/exits compared to drivers who decide to stay on the current route. It should be noted that this behavior was primarily affected by the driver's decision, and not necessarily by the real-time information, as it can be observed in the no- information scenario as well (unlike $\mathcal{J}^{\beta}$, $\mathcal{C}^{\alpha}$ is non-zero for the no-information scenario). The lack of any significant effects of information characteristics-based variables on cognitive inattention further supports this premise. In addition, the marginal effects of the latent cognitive effects indicate that they can have considerable impacts on drivers' route choices if they vary significantly. Driver cognition are affected by several factors, including some that are not modeled in this study (e.g., trip purpose and weather conditions), and thus, it is important to incorporate them in designing and disseminating real-time information.

This study provides valuable insights for several stakeholders. First, the proposed model incorporates the effects of information characteristics (i.e., source, amount, sufficiency, and content), route characteristics (i.e., freeway route or arterial route), and situational factors (i.e., downstream traffic congestion) on route choice decision. This enables traffic operators to better predict drivers' route choices under information provision, and thereby, to design information dissemination strategies for managing network traffic flows more effectively. Second, information service providers and auto manufacturers should factor the impacts of certain driver attributes, driving environment complexity, and information characteristics (i.e., source and amount) on drivers' cognitive effort and cognitive inattention while designing information and its delivery systems to enhance road safety and user experience. Third, the various effects of information and route characteristics on driver cognition and route choice behavior can be used by transportation planners to strategize the development of future ATIS infrastructure. Fourth, the results show that certain driver attributes (i.e., gender) affect drivers' route choices indirectly through the latent information-induced cognitive effects, which provides opportunities for information service providers and traffic operators to collaborate for designing and disseminating personalized information considering driver attributes to achieve their objectives (i.e., enhanced user experience, improved road safety, and better route choice predictions).

3.5 Concluding comments

This study proposes a hybrid route choice model that incorporates latent cognitive effects induced by real-time travel information provision and the effects of several directly-measurable explanatory factors. The latent effects were estimated using non-intrusive driver physiological (i.e., EEG) data instead of subjective self-reported data, thereby avoiding several memory and reporting biases. The model was calibrated using data from elaborate driving simulator experiments designed to elicit realistic route choice behavior under different information characteristics by using a network-level setup and a point-based reward system for participation compensation. The results illustrate the effects of two latent cognitive effects on the route choice behavior: cognitive effort to process and perceive real-time information, and cognitive inattention towards the road environment. The results also highlight the effects of information characteristics (i.e., source, amount, sufficiency, and content), route characteristics (i.e., freeway route or arterial route), and situational factors (i.e., downstream traffic congestion) on route choice decision. For reasons discussed in the previous section, only limited impacts were observed in terms of drivers' sociodemographic characteristics.

This study demonstrates the efficacy of physiological measures to estimate latent cognitive effects of real-time travel information, and subsequently to use them to predict drivers' route choices. Further, as summarized in the previous section, the study results provide valuable insights to multiple stakeholders, including traffic system operators, information service providers, auto manufacturers, and transportation planners.

This study can be extended by using other physiological measures collected through driver monitoring systems as such systems mature and enter the market. Future efforts should also focus on validating the proposed model in more complex road networks with other types of information sources and validate it using real-world data. This can enable the development of integrated in-vehicle driver monitoring and information systems that traffic operators and real-time information service providers can leverage to manage traffic network performance by influencing drivers' route choices.

Some potential future research directions include the following. First, the study sample is biased towards younger participants, which may affect the generalizability of the study results. This could partly explain why we did not find any statistically significant effects of age on the latent cognitive effects or on the route choice utility. Future experiments can include a sample that is more representative of the general population. Second, panel data effects manifesting from repeated measurements are not considered here, and can provide opportunities for useful insights. Third, situational factors such as traffic density and trip purpose are not varied in the current study. These factors may have interaction effects with the driver's physiological indicators and can be addressed through further experiments.

4. EVALUATING THE IMPACTS OF DRIVER'S PRE-WARNING COGNITIVE STATE ON TAKEOVER PERFORMANCE UNDER CONDITIONAL AUTOMATION

4.1 Introduction

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

This study investigates the impacts of driver's pre-warning cognitive state (i.e., before the issuance of a takeover warning) on takeover performance under conditional automation. Section 4.1.1 presents a brief literature review related to driver cognition in automated vehicles and discusses the importance of factoring driver's pre-warning cognitive state in takeover performance. Further, to benchmark the role of driver's pre-warning cognitive state in takeover performance, a comprehensive metric is required to capture the overall driving performance and road safety during the takeover event. However, most existing studies ignore the interdependencies between the associated driving performance indicators (e.g., minimum time-to-collision and maximum deceleration) by analyzing them independently. Hence, we propose a novel comprehensive takeover performance metric, Takeover Performance Index (TOPI), that combines multiple driving performance indicators representing three aspects of takeover performance: risk of collision, the intensity of the driver's response, and trajectory quality.

Next, we discuss the literature on driver's cognitive states and their role in takeover performance. In Section 4.1.2, we review various indicators used to assess takeover performance, discuss related shortcomings, and distinguish the TOPI metric from the prior efforts to overcome these shortcomings. Then, we summarize the study objectives and contributions in Section 4.1.3.

4.1.1 Driver cognition in automated vehicles

In partially automated vehicles, driver cognitive states such as passive fatigue and hypovigilance can lead to slower reactions to takeover warnings and/or unsafe driving maneuvers (Körber et al., 2015). Conditional automation further aggravates these issues by introducing NDRT-induced distraction and resulting decrease in situational awareness (Capalar & Olaverri-Monreal, 2018; Radlmayr et al., 2014). Previous studies have investigated the changes in driver's cognitive states during partially and conditionally automated driving using subjective self-reported surveys as well as objective physiological indicators, typically after encountering a takeover event or a similar critical situation (see de Winter et al., 2014 for a review). A few studies have used self-reported surveys to evaluate different aspects of driver cognition; for example, NASA Task Load Index (NASA-TLX) and Rating Scale Mental Effort (RSME) to assess mental workload (de Winter et al., 2014), Dundee Stress State Questionnaire (DSSQ) to assess task engagement and mind wandering (Heikoop et al., 2018; Körber et al., 2015), Karolinska Sleepiness Scale (KSS) to assess fatigue and drowsiness (Ignacio Solís-Marcos et al., 2017), and Situation Awareness Rating Technique (SART) to assess situational awareness (Tanshi & Soffker, 2019). However, self-reported surveys are conducted after the takeover event and suffer from several memory biases (e.g., misattribution and transience) (Schacter, 1999), which reduces their ability to accurately estimate the driver's cognitive state before and during the takeover event. Naujoks et al. (2018) partially addressed these issues by using two expert raters to observe recorded experiment videos to subjectively assess driver cognition (i.e., fatigue and workload) and motivation to engage in

NDRT during Level 3 automated driving. However, expert rater assessments are prone to several errors that arise from their subjective nature, such as the halo effect (Engelhard Jr, 1994).

To avoid the aforementioned limitations of subjective measures of driver cognition, objective physiological indicators, including eye-related metrics, skin conductance, and heart rate and its variability, have been analyzed to estimate the driver's cognitive state. Studies have shown that increased eye blink rate, increased eye blink duration, and decreased pupil diameter are correlated with vigilance decrement under partial automation (Körber et al., 2015). Drivers also exhibit a lower eye blink rate when facing a critical takeover situation compared to a non-critical situation under partial automation, likely due to a sudden increase in workload (Merat et al., 2012). Similarly, lower heart rate, reduced skin conductance, and increased percentage eye closure (PERCLOS) are associated with reduced driving workload (de Winter et al., 2014). Alrefaie et al. (2019) found that driver's heart rate spikes when they are prompted to take over vehicle control. Some studies have also analyzed brain electrical activity patterns measured using electroencephalogram (EEG) to estimate driver stress, attention, mental demand, and vigilance decrement (Lee & Yang, 2020; Ignacio Solís-Marcos et al., 2017). Despite evidence of the driver's cognitive state affecting takeover performance, previous studies focus on evaluating the changes in driver's cognitive state during and after a takeover event (de Winter et al., 2014) rather than analyzing the impacts of driver's pre-warning cognitive state on takeover performance. A few studies have manipulated driver's pre-warning cognitive states (e.g., attention and mental workload) in conditionally automated vehicles to investigate their effects on takeover performance by varying experimental driving conditions such as traffic density (Gold et al., 2018) and type of NDRT (J. Kim et al., 2018), or by controlling driver's cognitive state through sleep deprivation (Vogelpohl et al., 2019) or intoxication (Wiedemann et al., 2018). But these studies do not analyze the driver's pre-warning cognitive state immediately before a takeover event, which can significantly impact takeover performance. To address this gap, our study estimates the driver's pre-warning cognitive state by analyzing driver's neurophysiological indicators (i.e., brain electrical activity) measured using EEG in driving simulator experiments and explicitly models its impacts on takeover performance in conditionally automated vehicles. Although gathering EEG data in real-world driving is less practical compared to other physiological data (e.g., eye tracking and heart rate measures), this study uses EEG data as it can estimate a more detailed profile of driver cognition by analyzing electrical activity patterns in different regions of the brain (Abhang et al., 2016b; Agrawal et al., 2020), especially in laboratory settings. Thus, it can provide more comprehensive insights on the underlying factors that affect takeover performance, which may not be possible by using other physiological indicators. Auto manufacturers can use these insights to improve the design of fallback procedures in conditionally automated vehicles. It will also assist policymakers to incorporate drivers' cognitive aspects in developing policies that regulate the use of these vehicles. Previous studies have shown that several other factors such as type of takeover situation (Radlmayr et al., 2014), type of takeover warning (Lu et al., 2019), learning effects (Gold et al., 2018), and road and traffic conditions (Gold et al., 2016) affect takeover performance. In this study, we investigate the impacts of some of these factors, including the type of takeover warning and novelty in takeover experience (i.e., learning from driver's first experience with a takeover situation), on takeover performance. Further, the effects of age on takeover performance remain unclear in the literature, most likely due to the counterbalancing effects of slower processing and more cautious driving style with an increase in age (B. Zhang et al., 2019). Thus, we also analyze the interaction effects of age and its covariate (i.e., driving experience) with driver's pre-warning cognitive state to analyze their counterbalancing effects on takeover performance.

4.1.2 Takeover performance measures

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

Several studies have evaluated takeover quality to assess takeover performance using three aspects of driving performance: risk of collision, driver's response, and trajectory quality. First, related to collision risk, crash probability (Gold et al., 2018) and the number of collision occurrences (Olaverri-Monreal et al., 2018) have been used to estimate of risk of collision in takeover situations. Minimum time-to-collision (TTC) is another well-established metric to evaluate the risk of collision (Radlmayr et al., 2014), with a lower value of minimum TTC indicating a higher risk of collision. Other studies have used minimum space and time headways to quantify traffic safety during a takeover (Dogan et al., 2019; Wiedemann et al., 2018). Second, as driver's steering and braking responses have direct impacts on vehicle dynamics, several studies have analyzed driver response to evaluate takeover quality. Steering wheel-related interactions have been studied using frequency analysis, mean percentage change, standard deviation, and maximum value of steering wheel angle (Alrefaie et al., 2019; Dogan et al., 2019; Naujoks et al., 2019; Olaverri-Monreal et al., 2018). Brake pedal-related interactions have been analyzed using brake application probability, frequency of brake application, average longitudinal deceleration rate, and maximum longitudinal deceleration rate (Dogan et al., 2019; Gold et al., 2018; Körber et al., 2016; Olaverri-Monreal et al., 2018). Third, some studies have analyzed trajectory quality using the longitudinal and lateral aspects of vehicle trajectory. While longitudinal trajectory mainly informs about the risk of rear-end collisions, lateral trajectory informs about the risk of the vehicle drifting out of the road or collision with other vehicles in the side lanes. Previous studies have evaluated longitudinal trajectory quality using mean percentage change in vehicle speed, average speed, and minimum vehicle speed (Alrefaie et al., 2019; Happee et al., 2017; Naujoks et al., 2019), and lateral trajectory quality using maximum lateral acceleration, deviation of lateral road offset, and lane change time and speed (Dogan et al., 2019; Körber et al., 2016; Mok et al., 2015). Happee et al. (2017) used additional measures, including obstacle clearance, roadside clearance, and lateral overshoot (going past the target lateral position), to further evaluate the trajectory quality during a takeover event. Qualitative assessment of vehicle trajectories (e.g., visual inspection of trajectory plots) has also been used in past work (Gold et al., 2013).

In summary, while past studies have assessed takeover performance using multiple indicators, each indicator is often analyzed independently. Thus, they are limited in their ability to provide an overall assessment of takeover performance, especially from the perspective of takeover quality, as they ignore the interactions and interdependencies between these indicators. For example, a higher rate of longitudinal deceleration, which generally represents poor takeover performance, can result in a longer minimum TTC, which generally represents a good takeover performance. Radlmayr et al. (2018) proposed an integrative framework, called the take-over performance score or TOPS, that aggregates different takeover performance measures to three dimensionless parameters representing vehicle guidance (e.g., collision occurrence and minimum TTC), driver's mental processing (e.g., reaction time), and subjective ratings of takeover situation (e.g., perceived criticality and perceived complexity). However, TOPS has certain limitations: (i) as acknowledged by the authors, it represents differences in takeover performances and not necessarily their quality (good or bad), (ii) each parameter is calculated by linearly combining its corresponding indicators without accounting for their nonlinear relationships, and (iii) the vehicle guidance parameter combines generic vehicle dynamics indicators, and thereby, does not consider that different takeover situations entail different safe driving maneuvers. In this context, our study proposes Takeover Performance Index (TOPI), a novel comprehensive takeover performance metric that combines multiple driving performance indicators while partly accounting for their interdependencies. The proposed framework to compute TOPI is flexible and can be adapted to different takeover situations as discussed in Section 4.3.

4.1.3 Study objectives and contributions

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

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

The remainder of the paper is organized as follows. Section 4.2 discusses the experimental design and data collection procedures. Section 4.3 presents the framework for computing a comprehensive takeover performance metric. Section 4.4 discusses the statistical analysis methods used to evaluate the impacts of driver pre-warning cognitive state and other factors on takeover performance. Section 4.5 summarizes the analysis results and study findings. Finally, Section 4.6 concludes this paper by summarizing the study contributions and discussing their potential impacts on academia, industry, and government. We also discuss the limitations of this study and provide some future research directions in the final section.

4.2 Methodology

4.2.1 Apparatus

4.2.1.1 Driving simulator

The study was conducted using a medium-fidelity driving simulator (AVSimulation, 2020) with a full-scale driving cockpit and force feedback on the steering wheel, as shown in Figure 4.1. The driving environment with 120° field-of-view was projected on three LCD screens. Two side-view and rear-view mirrors are presented on the screens. A four-lane divided highway replicating the road curvatures of sections of the U.S. Interstate 65 (I-65) between West Lafayette, IN and Chicago, IL, was created using SCANeRStudio® 1.7 software. This was done to avoid generating a driving environment with a completely straight road, which may reduce the ecological validity of the study by artificially reducing the cognitive effort required to monitor the driving environment. The speed limit was set to 105 kph (about 65 mph). The driving environment also featured dynamic ambient traffic, which was slowly dissipated before the takeover event (see Section 4.2.2.1 for details). Driving data was collected at 20 Hz frequency.

4.2.1.2 Automated driving system

The study used a Level 3 automated driving system (ADS) that could perform both longitudinal and lateral control on the highway. It observed the speed limit and stayed in the right-most lane unless it had to pass slower-moving vehicles in the lane. It also provided two types of takeover warnings, an uncertainty alert and a takeover request (TOR). The warnings were delivered in the auditory format using two multimedia speakers that were positioned on each side of the driving cockpit below the screens. An uncertainty alert (presented as a single auditory chime) denoted that the ADS is unsure if it could navigate the road scene ahead and prompted the driver to redirect their attention on the road without the need for active intervention (non-mandatory takeover). A TOR (presented as three auditory chimes in quick succession) denoted a system failure that required the driver to resume vehicle control as soon as possible (mandatory takeover) to avoid potential road safety hazards. In this study, a TOR was always preceded by an uncertainty alert.

4.2.1.3 Non-driving related task (NDRT)

To simulate visual and manual distraction for the participants, an NDRT was developed that consists of a number transcription task delivered on a touchscreen tablet. The tablet was supported by a stand that was affixed to the base of the simulator and was positioned near the center console (see Figure 4.1). The participants completed a single NDRT task by inputting two six-digit numbers with the mathematical operator shown on the left side of the tablet screen into a calculator interface and pressing submit when done. No advanced numeracy skills were needed. Numeric characters were chosen over alphanumeric characters to avoid potential language-specific biases.

Figure 4.1 Driving simulator and NDRT

4.2.1.4 Electroencephalogram (EEG)

Participants' brain electrical activities were recorded during the simulated runs with a sampling rate of 256 Hz using the B-Alert X24 electroencephalogram (EEG) (Advanced Brain Monitoring, 2017). Nineteen EEG electrodes (or EEG channels) were placed according to the International 10-20 system (Klem et al., 1999), as shown in Figure 4.2. An EEG channel's prefix identifies its corresponding brain regions, that is, prefrontal lobe (Fp), frontal lobe (F), parietal lobe (P), temporal lobe (T), occipital lobe (O), and central sulcus (C). The EEG channel's suffix identifies its hemisphere, that is, left (1, 3, 5, 7), right (2, 4, 6, 8), and midline (z). A1 and A2 channels represent the mastoids that are used as references for measuring the power of the electrical signal at the EEG channels.

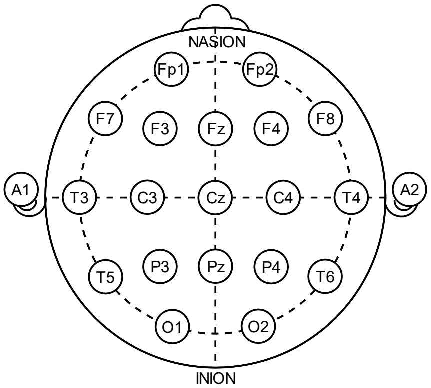

Figure 4.2 Locations of EEG channels - International 10-20 System (Wikipedia, 2019)

4.2.2 Experiment design and procedure

As a part of a larger study that investigates the effects of introductory information on driver's trust in automation and takeover performance, participants in our study were divided into two groups. Each group was shown an introductory video explaining the driver's role in each of the SAE levels of automation (SAE J3016, 2018), and a brief tutorial on operating the simulated ADS. The introduction video ended differently for the two groups, with one reminding the participants about their responsibility to ensure road safety and the other listing the benefits that might be achieved in the future with higher levels of automation. However, our study disregards this grouping as no statistically significant differences in takeover performance were found between the two groups (see Souders et al., 2020 for details).

Before the lab visit for the simulator experiments, participants completed an online survey that included a screening questionnaire (see Section 4.2.4 for the eligibility criteria), demographic information questions, and other behavioral/attitudinal questions (see Souders et al., 2020 for details). During the lab visit, participants signed an informed consent form and completed a practice run in the simulator that involved manually driving an automatic transmission vehicle in an urban environment with multiple intersections. This practice run also served as a screening procedure for participants with simulator sickness. Then, participants viewed the introduction video for their randomly assigned group. Neither the experimenter nor the participant knew about the assigned group (i.e., double-blind manipulation). Next, participants were equipped with a wearable eye-tracker (Dikablis Glasses 3; Ergoneers, 2018) and the EEG. Our study does not analyze eye-tracking data. Then, participants completed another practice run with the ADS and NDRT concurrently on a four-lane divided highway, to get acquainted with the ADS, its activation and deactivation procedures, and takeover warnings. In the practice run, drivers experienced both types of takeover warning multiple times, with a brief time of automated driving between two consecutive warnings, until they verbally confirmed that they are comfortable with handling the ADS. Traffic cones were used as obstacles to create safety-critical events that trigger the issuance of a takeover warning. In addition, each takeover warning was preceded by a voice message to prepare the participants and inform them about their expected response (i.e., pay attention to the road for an uncertainty alert, and take over manual control for a TOR).

Participants completed three experiment runs (approximately 10, 10, and 7 minutes, respectively) with moderate ambient traffic density (about 6-7 vehicles in a 500-meter radius). Each run culminated in a safety-critical event that was preceded by takeover warning(s) (see Section 4.2.2.1 for details). Participants were asked to activate the ADS as soon as possible after the start of a run. They were allowed to take over manual control of the vehicle at any time if they are concerned about road safety. However, they were informed that their final compensation for participation would depend on the number of correct responses to the NDRT, as well as road safety across all three runs. This was done to provide an incentive to disengage from driving and engage in the NDRT, which is expected in conditionally automated vehicles. Participants also completed a few surveys between runs and after the three runs that captured their trust in automation, perceived workload, and simulator sickness (see Souders et al., 2020 for details). Our study does not analyze data collected from these surveys. Finally, participants were debriefed and compensated for their participation. Although participants were informed that their amount of compensation depended on their performance in the NDRT and road safety, they received full compensation of $45 regardless of their performance. The experiment protocol was approved by the Purdue University's Institutional Review Board (protocol #1811021326).

4.2.2.1 Safety-critical events

Each of the three experiment runs culminated in a different safety-critical event. The first and third runs present a non-mandatory takeover event with a delayed lateral and longitudinal response from the ADS, respectively. The second run presents a mandatory takeover event with an ADS failure. Since the larger study focuses on drivers' trust in automation, the order of the runs was not randomized to control participants' learning experiences. The details of each event are as follows.

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

In the second run, the ego vehicle approaches a broken-down vehicle (0 kph) occluded by a slower-moving bus (35 kph). When the TTC with the broken-down vehicle is 8 seconds, the bus shifts lane, making the broken-down vehicle visible to the driver, and an uncertainty alert is issued. If the driver does not intervene by 4 seconds TTC, the ADS disengages and issues a TOR, thereby, making it mandatory for the driver to take over vehicle control to avoid a crash.

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

To ensure that there are no vehicles present during the takeover event other than the ego vehicle and the event vehicle(s), the ambient traffic was smoothly dissipated by changing the speed of ambient vehicles about 2000 meters before the takeover event.

4.2.3 Data preprocessing

Raw EEG signals are contaminated with low- and high- frequency noise known as artifacts. These artifacts can be generated due to physiological (e.g., eye or muscle movements) or non-physiological (e.g., presence of other electrical devices nearby) factors (Britton et al., 2016). We used the B-Alert software to remove the following artifacts from the raw EEG signals: electromyogram (muscle movements), eye blinks, excursions, amplifier saturations, and spikes (B-Alert, 2009). Then, the power spectral density of the EEG signal was computed by performing fast Fourier transformation over epochs of 1-second duration with 50% overlapping window. Next, EEG band powers were computed by averaging the power spectral density in four frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz), and beta (13-30 Hz).

Since the magnitude of EEG band power varies across individuals, we standardized the band powers by computing Z-scores for each participant to estimate the relative changes in their neurophysiological indicators, and thereby, cognitive state. The Z-score of EEG band power for an individual i at epoch t in run r is computed using Eq. (4.1), where X represents the EEG band power, and $\bar{X}_i$ and SD_i are the mean and standard deviation of the EEG band power for individual i, respectively, over all three runs.

$$Z_{tri} = \frac{X_{tri} - \bar{X}_i}{SD_i} \tag{4.1}$$

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

4.2.4 Participants

We recruited participants from the Greater Lafayette community in Indiana, USA, through advertisements in Purdue University's weekly email newsletter, paper fliers at community events, and word of mouth. Participation eligibility criteria included: (i) being at least 18 years of age, (ii) having a valid driver's license, (iii) having no predisposition to motion sickness, (iv) having no mental or physical impairments (self-reported), and (v) if over the age of 64, passing an over-the-phone pre-screen memory impairment test (Wechsler Memory Scale; Wechsler, 1997). In addition, participants were also asked to avoid the consumption of any medication or caffeine for at least 8 hours prior to the experiment as this may affect EEG patterns (Blume, 2006; Pritchard et al., 1995), and thereby reduce EEG data quality. A total of 134 drivers participated in the study. However, we used data from only 118 participants for the analysis, because 16 participants were excluded due to having invalid EEG data in at least one of the runs. The invalid EEG data was due to two possible reasons: (i) EEG equipment malfunction resulting in missing data, and (ii) problems in synchronizing the EEG data with the driving data due to missing timestamps. Figure 4.3 shows the age distribution (29.44 ± 14.15 years) of the participants grouped by gender (55 males and 63 females).

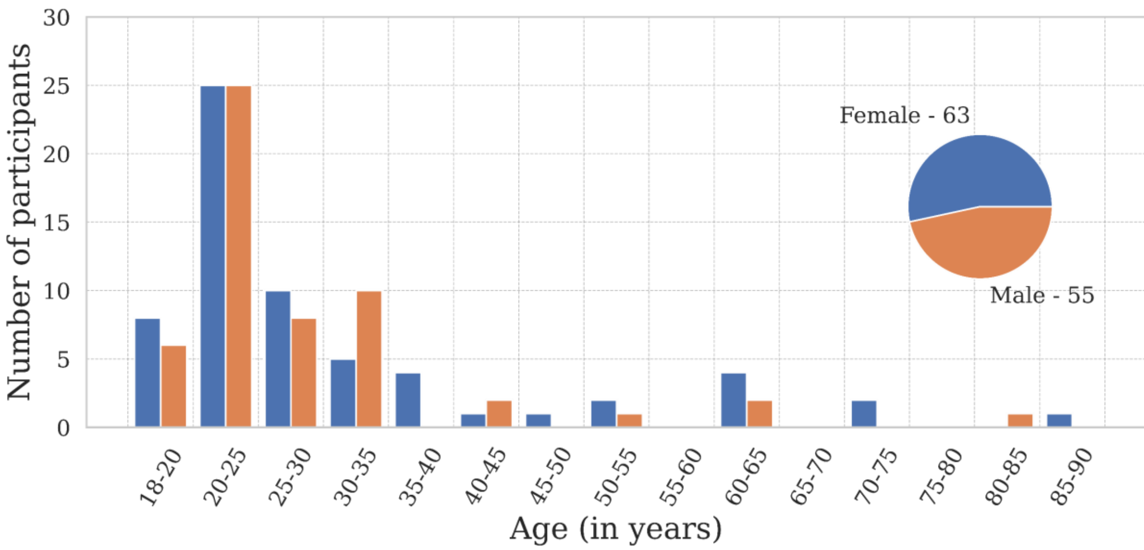

Figure 4.3 Age and gender distribution of the participants

4.3 Takeover Performance Index (TOPI)

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

First, we define a takeover performance sub-index (T_i) for each driving performance indicator i on a unit interval (i.e., a value between 0 and 1) using a sigmoid function, given by Eq. (4.2). We choose the sigmoid function because: (i) it is bounded between the unit interval, and therefore, normalizes the driving performance indicators to a common dimensionless scale, and (ii) its S-shape diminishes the effects of extreme cases (outliers), thereby making T_i more robust.

$$T_i = \frac{1}{1 + e^{-W_i(x_i - c_i)}} \tag{4.2}$$

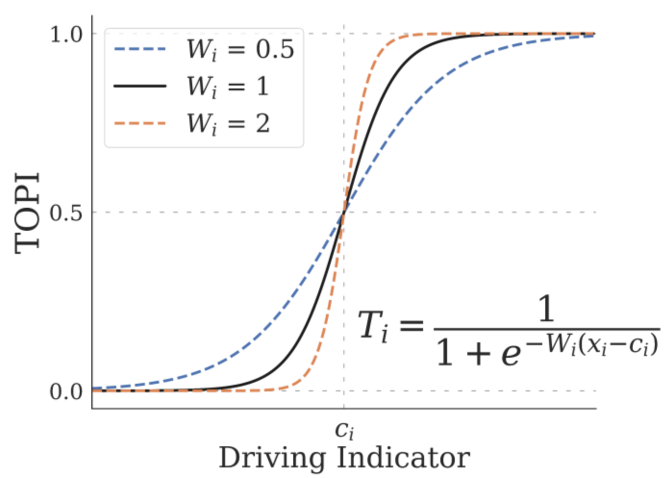

Figure 4.4 Sigmoid function

In Eq. (4.2), x_i is the value of the driving performance indicator i. c_i is the centering parameter that represents the indicator value at which T_i is equal to 0.5 (i.e., 50th percentile). W_i is the spreading parameter that controls the spread/curvature of the function. W_i can be back-calculated using Eq. (4.2) by substituting x_i with a reference value of driving performance indicator ($\tilde{x}_i$; spreading parameter reference) at a given T_i. In this study, we use $\tilde{x}_i$ at the 75th percentile of T_i (i.e., T_i equal to 0.75). Figure 4.4 illustrates the distribution of T_i for three different spreading parameters. The parameter values can be determined by using insights from the literature or by making reasonable assumptions in the context of the takeover event, as illustrated later in this section. For example, a smaller spread of deceleration rate may be preferred in congested traffic conditions to avoid rear-end collisions, while a larger spread may be acceptable in uncongested traffic. This mechanism enables the TOPI to adapt to different takeover situations by allowing the selection of appropriate driving performance indicators and their parameter values.

Next, we compute the TOPI value (T) by taking the geometric mean of takeover performance sub-indices for all driving performance indicators, as shown in Eq. (4.3). Since takeover performance sub-indices are defined on a unit interval, their geometric mean TOPI varies between 0 and 1, with a higher value of TOPI value representing a better takeover performance. Geometric mean is chosen over arithmetic mean as it is lower than the arithmetic mean, which implies that poor takeover performance sub-index (i.e., values closer to 0) of a single driving performance indicator will have a larger effect on the TOPI value. For example, a higher value of deceleration rate (typically representing a poor takeover performance), with a sub-index value closer to 0, can result in a longer minimum TTC (typically representing a good takeover performance), with a sub-index value closer to 1. However, their resulting TOPI value (geometric mean) will be closer to 0, indicating a poor takeover performance. Hence, by computing sub-indices of driving performance indicators using a non-linear (sigmoid) function and by combining them using the geometric mean, the TOPI partly captures the interdependencies between these indicators. Further, the TOPI provides a conservative estimate of takeover performance, which is suitable, and even preferred, for safety-critical situations. Therefore, the TOPI captures multiple aspects of takeover performance in a single, comprehensive metric, and thereby, is suitable to benchmark the effects of driver's pre-warning cognitive state on the overall takeover performance.

$$T = \sqrt[n]{\prod_{i}^{n} T_i} \tag{4.3}$$

In this study, we use four driving performance indicators to represent the three aspects of takeover performance. The risk of collision is represented by minimum TTC, where a longer minimum TTC indicates a lower risk of collision, and thereby, a better takeover performance. The intensity of driver's response is represented by maximum deceleration rate and maximum steering wheel angle, both of which are negatively correlated with the takeover performance. Trajectory quality has two aspects: longitudinal and lateral. However, the longitudinal trajectory quality is correlated with the risk of collision and is captured by minimum TTC. To assess the lateral trajectory quality, we define a new driving performance indicator, maximum lateral trajectory deviation (LTD), which is defined as the maximum lateral deviation from the ideal lateral trajectory in the context of a takeover event. In the takeover events designed in this study, the ego lane of the driver is blocked either by a slower-moving bus or by a broken-down vehicle. Thus, ideally, the driver first needs to maneuver the vehicle to the center of the adjacent lane (i.e., the target lane), and then, return to the center of the ego lane after passing the blocking vehicle. The maximum LTD is computed as the sum of the two maximum lateral deviations corresponding to these two maneuvers, as given by Eq. (4.4). The first component in Eq. (4.4) is the maximum lateral deviation from the center of the target lane (ΔL_{target}) when the vehicle is moving to the target lane, as illustrated in Figure 4.5. It captures the maximum lateral deviation due to: (i) lateral undershoot, which happens when the vehicle does not reach the center of the target lane, and thereby, has an increased risk of a side collision with the blocking vehicle, and (ii) lateral overshoot, which happens when the vehicle goes past the center of the target lane and has an increased risk of going off the road. The second component in the Eq. (4.4) is the maximum lateral deviation from the center of the ego lane (ΔL_{ego}) due to overshooting in the other direction when the driver is returning to the ego lane after passing the blocking vehicle, as illustrated in Figure 4.5.

$$\text{LTD} = \Delta L_{\text{ego}} + \Delta L_{\text{target}} \tag{4.4}$$

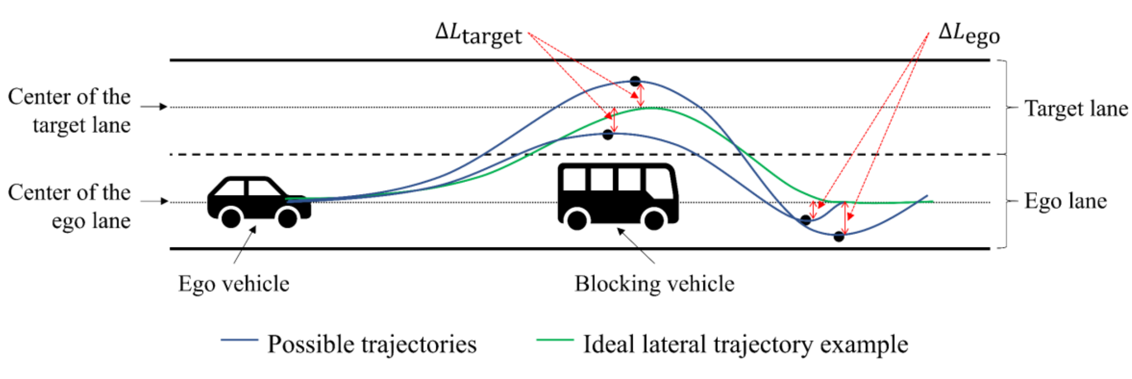

Figure 4.5 Components of maximum lateral trajectory deviation

The parameter values to compute the individual takeover performance sub-index for each of the four driving performance indicators are determined as follows. For minimum TTC, Minderhoud and Bovy (2001) discussed that while the TTC of 3 seconds may be optimal (i.e., least false alarms) for collision warning systems, advanced driver assistance systems can implement even lower TTC values (e.g., 2 seconds). We use 2.5 seconds and 1 second as c_i and $\tilde{x}_i$, respectively, for minimum TTC. McGee et al. (2012) reported that most handbooks recommend deceleration rates between 3 m/s^2 and 4.5 m/s^2 for designing traffic signals, with 3.4 m/s^2 considered as a comfortable deceleration rate. Thus, to assess the intensity of the driver's response, we assume the values of c_i and $\tilde{x}_i$ for maximum deceleration rate to be 4.5 m/s^2 and -2 m/s^2, respectively. The negative spreading parameter value means that higher values of the driving performance indictor lead to a lower TOPI value. We did not find recommended estimates for the maximum steering wheel angle in the literature, as it is highly situation-dependent. Thus, we assume c_i and $\tilde{x}_i$ for maximum steering wheel angle to be 40 degrees and -10 degrees, respectively. These estimates are based on the visual inspection of the maximum steering wheel angle distribution of the study data. Likewise, for maximum LTD, we assume c_i and $\tilde{x}_i$ as one-fourth and negative one-eight of the lane width, respectively. The lane width in the simulated driving environment is 3.66 meters. The parameters values used in this study are shown in Table 4.1.

Table 4.1 Parameter values for computing takeover performance index

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

In our study, the driving performance indicators are computed using driving data within a 15-second time window after the issuance of the uncertainty alert to evaluate takeover performance. The TOPI is not calculated for runs in which participants did not take over vehicle control or intervened before an uncertainty alert was issued. The TOPIs for 19 runs were excluded due to an unexpected error (a rogue vehicle appearing in front of the ego vehicle) during the takeover event.

Based on these observations, we calculated the TOPI for 287 runs across 118 participants. Figure 4.6 illustrates the distribution of the TOPI for all participants. The zero-inflated TOPI is due to the poor takeover performance by several participants, especially in their first run.

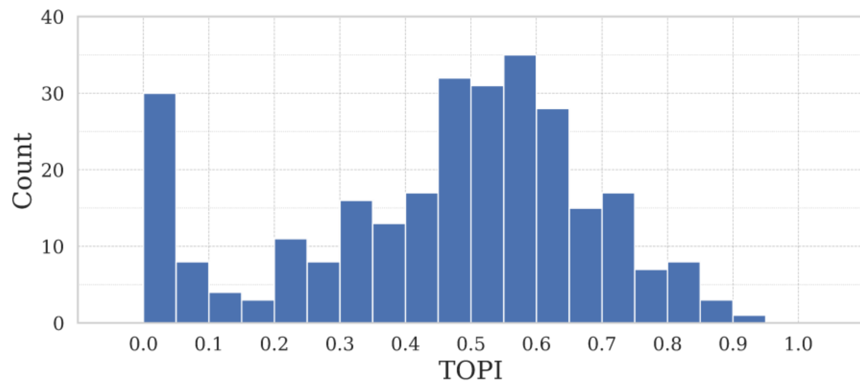

Figure 4.6 Distribution of takeover performance index

4.4 Data Analysis

As stated earlier, the study investigates the impacts of driver's pre-warning cognitive state on takeover performance using physiological indicators (EEG average powers). We draw insights from the neuroscience literature to link EEG average powers in different EEG bands and different regions of the brains with specific aspects of driver cognition. Thus, we use EEG average powers as indicators of driver's pre-warning cognitive state to analyze its effects on takeover performance. We also examine the effects of driver attributes such as age and driver experience, and their interaction effects, with driver's pre-warning cognitive state on takeover performance. In addition, we analyze the effects of additional factors, including novelty in takeover experience and type of takeover warning, that may affect takeover performance. Due to the shortcomings of existing takeover performance measures (as discussed in Section 4.1.2), we propose a TOPI that provides a comprehensive metric that is suitable to benchmark the effects of driver's pre-warning cognitive state (using EEG average powers), driver attributes, and other factors on takeover performance.

We estimate linear mixed models (LMMs) to analyze the effects of the aforementioned factors on the TOPI. There are two key benefits of using LMM: (i) it accounts for the non-independent or correlated errors that arise due to panel data (multiple runs from the same participant), and (ii) unlike Analysis of Variance (ANOVA), it is robust to missing data and can provide unbiased results without the need for listwise deletion (i.e., deleting entire data for a participant if a single data point is missing). Therefore, it enables us to use data for participants who did not take over manual control of the vehicle (i.e., TOPI is not calculated) in all three runs.

In this study, we estimate 76 LMMs for each of the four EEG bands and nineteen EEG channels independently. The basic form of estimated LMMs is given by Eq. (4.5).

$$T^2 = \beta_0 + \beta_{nov} + \beta_{TOR} + \beta_{EEG} + \beta_{age} + \beta_{exp} + \beta_{EEG*age} + \beta_{EEG*exp} + \gamma + \varepsilon \tag{4.5}$$

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

Previous studies have reported a continuous (linear or logarithmic) positive trend in driver's takeover performance over successive experiment runs due to learning effects (Gold et al., 2018; Happee et al., 2017). However, our preliminary data analysis indicates a strong positive stepwise trend instead of a continuous trend in takeover performance due to learning effects after the driver's first experience with a takeover situation (i.e., novelty effects), as illustrated in Figure 4.7. Understanding the learning/novelty effects in takeover performance can provide insights to policymakers for developing operator training programs and driver licensing strategies for conditionally automated vehicles. The preliminary data analysis also shows a lower TOPI value in the presence of a TOR in the second run. These results can aid auto manufacturers to design takeover warning systems that improve takeover performance, as from their perspective poor takeover performance will not only reduce road safety, but will also negatively impact drivers' user experience with and trust in the ADS.

Driver's age is treated as a continuous variable while driving experience is defined as an indicator variable. Participants having a driver's license for more than 5 years are considered as experienced drivers and their counterparts as novice drivers. Although there is a natural correlation between age and driving experience, the data show a good mix of age and driving experience among drivers between 20 to 35 years of age, as shown in Figure 4.8.

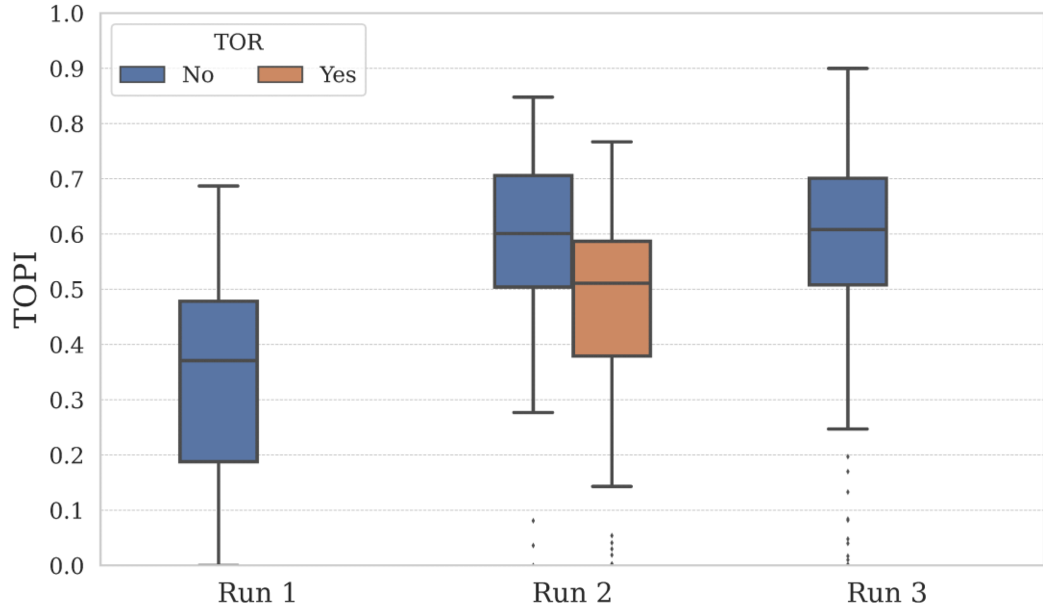

Figure 4.7 Boxplot of takeover performance index across runs and TOR

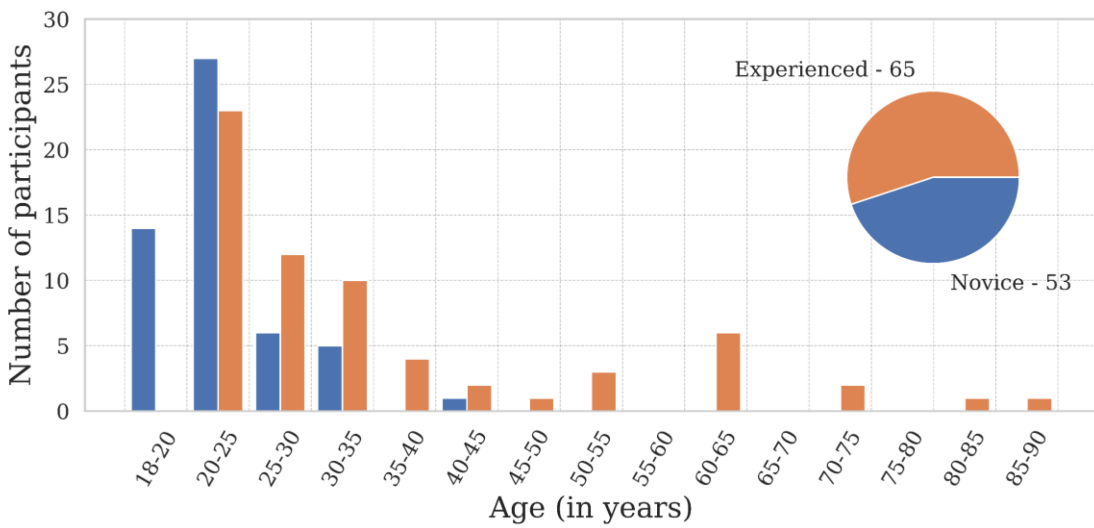

Figure 4.8 Age and driving experience distribution of the participants

We assess the relative goodness-of-fit of the model by comparing its Akaike Information Criterion (AIC) with the AIC of the null model (i.e., the model with intercept and random effects only), which is given by Eq. (4.6). A lower AIC value indicates a better goodness-of-fit. We also test the assumption of normality of the model residuals using the Shapiro-Wilk test, which tests the null hypothesis that the sample is normally distributed. We use the significance level (p-value) of 0.05 to reject the null hypothesis of the Shapiro-Wilk test.

$$T^2 = \beta_0 + \gamma + \varepsilon \tag{4.6}$$

4.5 Results and Discussion

4.5.1 Model preliminaries

The AICs of all 76 estimated LMMs (for 4 EEG bands and 19 EEG channels) are significantly lower than that of the null model, indicating a relatively better goodness-of-fit fit. The mean AIC for the estimated LMMs is -227.749 (minimum: -237.322; maximum: -222.925) and the AIC for the null model is -140.196. The assumption of normality of residuals is satisfied (at 0.05 significance level) for all estimated LMMs with p-values for the Shapiro-Wilk test ranging between 0.055 and 0.254. The model intercepts (β_0) for all estimated LMMs are found to be statistically significant ($p < 0.01$) with a mean value of 0.412 (minimum: 0.386; maximum: 0.433). The random effects (γ) variance is positive across all models.

A heatmap-based visualization of the coefficients for the estimated LMMs is presented in Figure 4.9. For a given model (i.e., specific EEG channel and EEG band), the value of a coefficient is presented at its corresponding coefficient row, EEG band column, and EEG channel location (refer to Figure 4.2). The red color indicates a positive coefficient value, while the blue color indicates a negative coefficient value. The statistical significance levels of 0.01 (significant) and 0.05 (marginally significant) are shown as solid black circles and hollow circles, respectively.

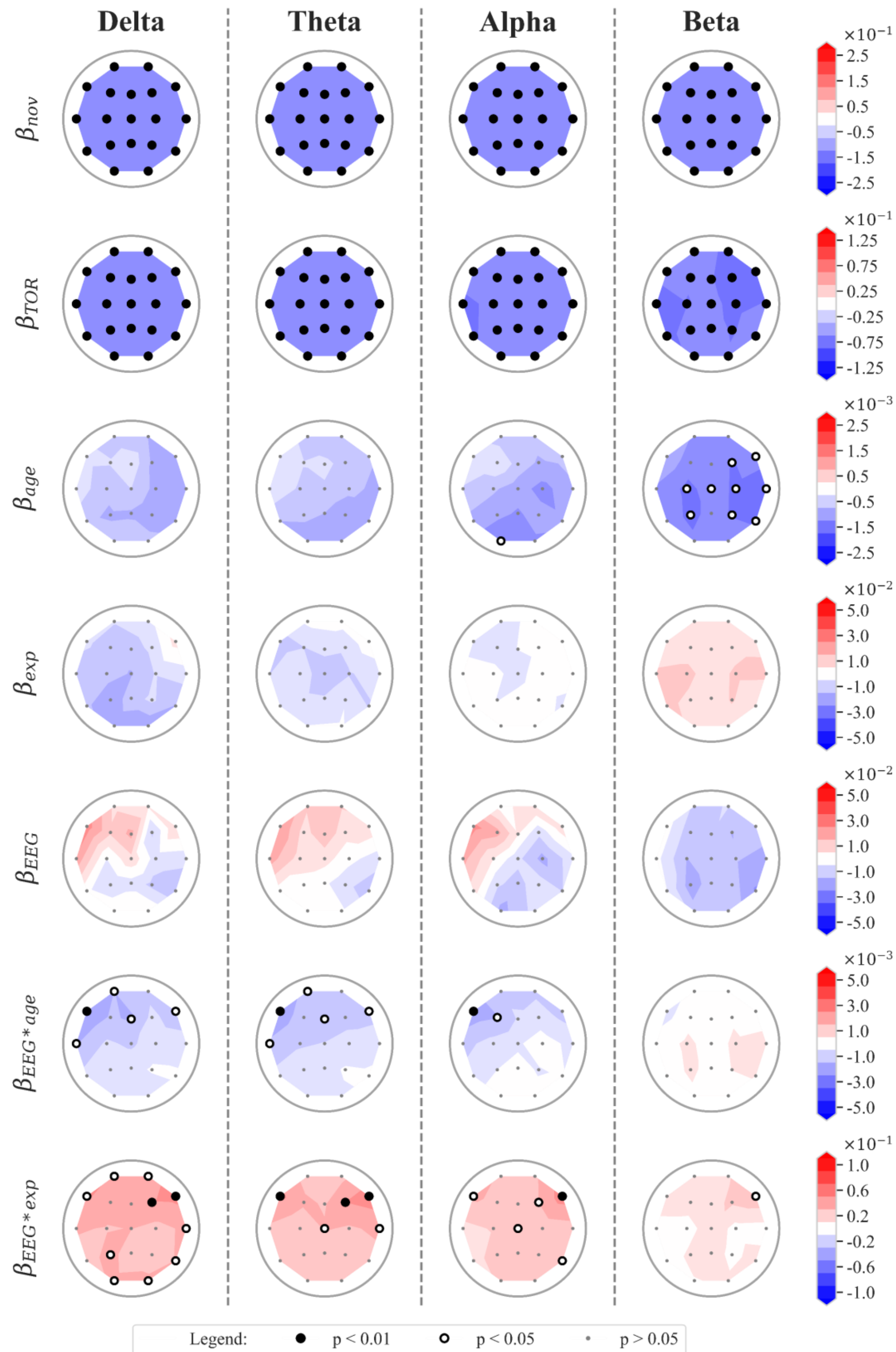

Figure 4.9 Coefficients of the estimated linear mixed models for 19 EEG channels and 4 EEG bands

4.5.2 Effects of age

The mean coefficient of age (β_{age}) for all estimated LMMs is -0.0014 (minimum: -0.0025; maximum: -0.0003). Although the main effect of age is only marginally significant ($p < 0.05$) in some of the estimated LMMs, overall, it indicates a decrease in the TOPI value with age. These results are somewhat inconsistent with the findings from a previous study by Gold et al. (2018), which reported a linear increase in minimum TTC with age. However, unlike the TOPI, their analysis did not consider the intensity of the driver's response, and thus, only partially explains the impacts of age on the overall takeover performance. Körber et al. (2016) reported significantly higher minimum TTC for older drivers, but marginally stronger brake reactions, which have counteracting effects on the proposed TOPI. They also argued that even though the expected cognitive decline suggests an increase in reaction times with increasing age, years of experience with driving and resulting expertise may have affected the task performance in a naturalistic driving task. Our study addresses these concerns by explicitly analyzing the impacts of driving experience (a proxy for task expertise) and driver cognition, as discussed hereafter.

4.5.3 Effects of driving experience

The coefficients of driving experience (β_{exp}) are found to be statistically non-significant for all the estimated LMMs with a mean value of -0.005 (minimum: -0.033; maximum: 0.019). There is limited research on explicitly modeling the impacts of driving experience on the TOPI, as most studies discuss it indirectly as a covariate of age. Our results indicate that driving experience with human-driven vehicles did not have significant primary effects on takeover performance in conditionally automated vehicles. However, we did find their significant interaction effects with driver's pre-warning cognitive state, as discussed in Section 4.5.4.3.

4.5.4 Effects of driver's pre-warning cognitive state

4.5.4.1 Main effects

The main effects of EEG average power (β_{EEG}) on the TOPI are found to be statistically non-significant for all EEG channels and across all EEG bands, as illustrated in Figure 4.9. Two key insights can be drawn from these results. First, we infer driver's pre-warning cognitive state directly from EEG average powers, and thereby, the non-significant values of β_{EEG} indicate that driver's pre-warning cognitive state did not have significant primary effects on the TOPI. Second, since the TOPI provides a single, comprehensive metric to capture the overall driving performance during a takeover event, the results indicate that drivers' pre-warning cognitive state may not directly affect the overall takeover performance. However, the overall effects of pre-warning cognitive state, including its interaction effects with age and driving experience, on the TOPI are found to be statistically significant, as discussed next.

4.5.4.2 Interaction effects with age

The coefficients of interaction between EEG average power and age ($\beta_{EEG*age}$) are mostly negative for the estimated LMMs, as illustrated in Figure 4.9. They are statistically significant or marginally significant for the delta, theta, and alpha bands in the left frontal and temporal lobes. These results suggest that certain cognitive states that are manifested as higher delta, theta, and alpha band powers primarily in the frontotemporal cortex have significantly higher negative impacts on the TOPI with increasing age. In the driving context, existing literature has linked higher delta band power in the frontal lobe (Jap et al., 2009; Morales et al., 2017) and higher theta band power in frontal, temporal, and in other regions of the brain (Jap et al., 2009; Shamsul et al., 2014) with mental fatigue induced by long monotonous driving. Similarly, Lal et al. (2003) reported an overall increase in delta, theta, and alpha activities with an increase in driver fatigue. In a non-driving context, Harmony (2013) reported higher delta band power in frontal and centroparietal regions of the brain while performing tasks that require increased attention to internal processing (e.g., mental calculation) or memory retrieval (e.g., semantic task). Aftanas and Golocheikine (2001) associated higher theta but lower alpha band powers in the frontal cortex with the states of internalized attention or positive emotional states. Abhang et al. (2016) associated higher theta band power with an increase in inward focus, drowsiness, or deeply relaxed state, and higher alpha band power with a state of passive attention. Thus, the TOPI value for drivers significantly decreases with age when they are in a relative state of fatigue, drowsiness, passive attention, or low alertness level. In addition, the NDRT implemented in this study does not require mental calculation or memory retrieval and was considered to be "monotonous and boring" by most participants, which could have contributed to inducing these cognitive states.

4.5.4.3 Interaction effects with driving experience

In contrast to the interaction effects of age, the coefficients of interaction between EEG average power and driving experience ($\beta_{EEG*exp}$) are mostly positive. The coefficients are statistically significant or marginally significant in several regions of the brain for the delta band and in the frontal and temporal lobes for the theta and alpha bands, as illustrated in Figure 4.9. These results show that experienced drivers have a better TOPI value compared to novice drivers in a state of fatigue, drowsiness, passive attention, or low alertness level. Given our sample characteristics (see Figure 4.8), this illustrates a counteracting effect of age and experience, especially for middle-aged drivers, where the former results in cognitive decline while the latter improves the anticipation of and response towards unexpected events. Further, a higher delta band power in the parietal cortex has been associated with performing visually complex tasks compared to mentally complex tasks (Wilson, 2002). Thus, the marginally significant delta power in this region suggests that engaging in visually distracting NDRTs could have an adverse effect on the takeover performance of novice drivers.

4.5.5 Effects of novelty in takeover experience

The coefficients of novelty effect (β_{nov}) are found to be statistically significant ($p < 0.01$) for all the estimated LMMs, as illustrated in Figure 4.9, with their mean value equal to -0.218 (minimum: -0.221; maximum: -0.216). These results indicate that participants performed poorly (i.e., a lower TOPI value) in their first realistic takeover situation, even with a hands-on practice session with the ADS, compared to future events. These findings suggest that a simplified or non-critical takeover practice may not be sufficient to prepare drivers for real-world takeover situations. Further, the driving duration and takeover event details were varied in each run, with the aim of reducing the expectation of the takeover event in future runs. The stepwise novelty effect on the TOPI found in this study is partly comparable to the positive logarithmic effect of repetition on minimum TTC found by Gold et al. (2018).

4.5.6 Effects of type of takeover warning

The coefficients of TOR presence (β_{TOR}) are found to be statistically significant ($p < 0.01$) for all estimated LMMs, with a mean value of -0.110 (minimum: -0.115; maximum: -0.103). The negative coefficient indicates a lower TOPI value if a TOR is issued in the second run. This could be because a TOR is issued with a 4-second time budget compared to an 8-second time budget for an uncertainty alert, which may stimulate a sense of urgency and elicit an intense response from the driver resulting in a poor TOPI value.

4.5.7 Study findings and insights

The results show marginally significant main effects of age, but no statistically significant main effects of driving experience on the TOPI. They indicate a decrease in the TOPI value with age, most likely due to an age-related decline in reaction time and quality. The lack of significant main effects of driving experience on the TOPI suggests that experience with human-driven vehicles does not directly entail a better takeover performance in conditionally automated vehicles; however, it does benefit drivers in responding to takeover situations under certain driver's pre-warning cognitive states, as discussed hereafter. In addition, although the direct effects of the driver's pre-warning cognitive state were found to be statistically non-significant, its interaction effects with individual characteristics (i.e., age and driving experience) were found to be statistically significant. While certain cognitive states such as fatigue, drowsiness, passive attention, and low alertness had significantly worse impacts on takeover performance of older drivers compared to younger drivers, experienced drivers performed better under such cognitive states compared to novice drivers. Since age and driving experience are typically correlated, this provides a viable explanation for the widely varying results related to the effects of age on takeover performance in the existing literature. The results also suggest that experienced drivers can potentially have a better TOPI value compared to novice drivers while engaged in a visually distracting NDRT. These differences in the impacts of NDRT-induced distraction on takeover performance between drivers with varying driving experience highlight that a simple, one-size-fits-all approach may not work in designing regulations for using conditionally automated vehicles. A uniform regulation may be too restrictive and reduces the potential benefits of these vehicles to several drivers, or it may overestimate the abilities of some drivers to respond to critical takeover situations that may pose a risk to road safety. Policymakers and regulatory agencies can use these insights to identify the most vulnerable subgroups of the population based on driver attributes during the transitionary period towards higher levels of automation, and develop focused operator training programs and driver licensing strategies that make the transition smoother and safer. The study insights can also aid them to incorporate the interactions between driver attributes and cognitive aspects of using NDRT while devising policies that regulate the use of conditionally automated vehicles.

In this study, we found that driver's takeover performance improved significantly in the latter experiment runs after experiencing a realistic takeover situation in the first run. This shows that practicing taking over vehicle control in a simplified environment (practice run) did not help the drivers much. The novelty of experiencing a takeover situation can have a significantly worse impact in real-world driving situations compared to simulated driving as conditions can be more complex and uncertain in nature. These results have important implications for policymakers to develop operator training programs and driver licensing strategies for conditionally automated vehicles as traditional methods may fall short when preparing the public for operating these vehicles.

The effects of type of takeover warning suggest that waiting for a TOR in a graded warning system rather than taking over vehicle control after an uncertainty alert can result in significantly worse takeover performance. This shows that the drivers who followed the system instructions faced a more dangerous situation compared to their counterparts. Such experiences can reduce drivers' trust in automated vehicles (i.e., resuming manual control of the vehicle when it is not required), which can consequently lead to underutilization of the system. Although this study did not compare the impacts of issuing a TOR that is not preceded by an uncertainty alert or the effects of different time budgets for TOR on takeover performance, it illustrates the influence of takeover warning system design on driver behavior and performance in conditionally automated vehicles. This has key implications for auto manufacturers and ADS designers as automated vehicle technologies are introduced in the market, especially related to road safety and trust/adaptability with these systems.

4.6 Concluding Comments

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

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

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

The study can be extended in the following ways. First, we did not control for the order effects of experiment runs. Controlling these effects in future experiments may provide better insights regarding the impacts of driver's pre-warning cognitive state on takeover performance. Second, the current analysis does not include participants who took over vehicle control before the issuance of a takeover warning. Future research can develop mechanisms to continuously analyze driver's cognitive states to investigate whether these participants were more attentive due to their greater cognitive abilities or due to the lack of trust in the ADS. Third, although having a sample comprising of mainly younger adults enables us to better understand the effects of age and driving experience, future studies can include a more representative sample of the general population to improve the generalizability of the results.

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

5. EVALUATING THE IMPACTS OF SITUATIONAL AWARENESS MENTAL STRESS ON TAKEOVER PERFORMANCE UNDER CONDITIONAL AUTOMATION

5.1 Introduction

SAE Level 2 or partially automated vehicles have been on public roads for some time. These vehicles assist drivers with certain dynamic driving tasks such as lane-keeping and headway-maintenance to reduce their driving effort. Unlike partially automated vehicles that expect continuous supervision by drivers, SAE Level 3 or conditionally automated vehicles can control all aspects of the dynamic driving task and allow drivers to engage in non-driving related tasks (NDRTs) (SAE J3016, 2018). Even though drivers are not expected to monitor the vehicle under conditional automation, they are required to immediately take over vehicle control if it issues a takeover warning for venturing out of its operational bounds or for experiencing a system failure. This leads to several concerns regarding the driver's ability to safely resume vehicle control due to NDRT-induced distraction and the resulting loss in situational awareness (SA) (de Winter et al., 2014). Further, like in partially automated vehicles, drivers may also exhibit mental underload, vigilance decrement, and passive fatigue in conditionally automated vehicles after a sustained period of automated driving, which can negatively impact their takeover performance (i.e., resuming manual control after a takeover request) (Körber et al., 2015; Young & Stanton, 2002). Therefore, it is imperative to investigate drivers' mental state (hereafter referred to as "driver state") using human factors constructs such as SA and mental stress that may affect their takeover performance in conditionally automated vehicles. A comprehensive understanding of the impacts of driver state on takeover performance can help auto manufacturers to devise mechanisms (e.g., takeover warning system design) to manage driver state in automated vehicles, and thereby, mitigate its adverse effects on road safety and user experience.

Previous studies have evaluated driver state in automated vehicles using self-reported subjective surveys (offline measures); for example, Situation Awareness Rating Technique and Situation Awareness Global Assessment Technique to assess SA (Franz et al., 2015; Large et al., 2018), NASA Task Load Index and Rating Scale Mental Effort to assess workload (Dogan et al., 2019; Yoon & Ji, 2019), and Dundee Stress State Questionnaire to assess mental stress (Heikoop et al., 2018). The drawbacks of these methods, however, are that they are either intrusive (if conducted during the experiment), impractical for real-world applications, or subjected to several memory biases (Nguyen et al., 2019; Spector, 1994).

To avoid the aforementioned limitations of subjective measures, several studies have evaluated driver state using objective physiological indicators. Physiological indicators used to assess SA mainly consist of eye-tracking measures such as horizontal gaze dispersion (Louw & Merat, 2017), blink frequency (Radlmayr, Briich, et al., 2018), road attention ratio (Petersen et al., 2019), and on-road glance frequency and duration (Zeeb et al., 2015). Workload and mental stress have been analyzed using a variety of physiological data, including eye-tracking (e.g., pupil diameter, percentage of time with eyes closed, and blink frequency) (de Winter et al., 2014; Merat et al., 2012), cardiovascular activity (e.g., heart rate and its variability) (Alrefaie et al., 2019; Heikoop et al., 2018), skin conductance (M. Choi et al., 2018), and electroencephalography (I. Solís-Marcos & Kircher, 2018). Some studies have also indirect and less precise methods, including NDRT performance (Petersen et al., 2019) and verbal protocol analysis (where drivers say out loud whatever they are thinking at the moment) (Heikoop et al., 2018), to assess SA in automated driving. Recent advances in in-vehicle driver monitoring systems are providing opportunities to utilize physiological data for estimating driver state in real-time. In this context, our study investigates the efficacy of driver physiological indicators that can be obtained from in-vehicle driver monitoring systems in estimating driver state, and analyzes their impacts on takeover performance under conditional automation. Specifically, we use eye-tracking measures, including on-road glance rate (i.e., number of eye glances at the road per time unit) and road attention ratio (i.e., percentage of time spent glancing at the road), as physiological indicators of driver's SA during the automated driving. On-road glance rate is used because it measures how frequently the driver is monitoring the road and, thereby, how frequently they obtain updates on the dynamic road environment. Similarly, road attention ratio is used because it measures the ratio of the time duration the driver is monitoring the road compared to looking away from the road and, hence, informs on the level (assuming it is proportional to time) at which they monitor the road environment. We also use pre-warning normalized heart rate and the change in normalized heart rate after the takeover warning as indicators of mental stress immediately before and the change in mental stress after the takeover warning, respectively. Heart rate is used as it is a reliable indicator of mental stress (Taelman et al., 2008). Further, we normalize it to alleviate the individual differences in the base heart rate.

Most existing studies analyze the effects of driver state on takeover performance by manipulating experimental conditions such as NDRT (Yoon & Ji, 2019), traffic density (Gold et al., 2016), and driver impairment (e.g., fatigue and alcohol) (Kreuzmair et al., 2017; Wiedemann et al., 2018). However, these studies do not explicitly analyze the effects of driver's pre-warning state on takeover performance. In our previous work (Agrawal & Peeta, 2020), we used brain electrical activity patterns recorded using an electroencephalogram (EEG) to create a detailed profile of driver's pre-warning cognitive state, which cannot be done by using eye-tracking and heart rate measures, and analyzed its impacts on takeover performance. However, this study focuses on eye-tracking and heart rate measures because, unlike EEG-based measures, they can be collected via in-vehicle driving monitoring systems, and thereby, have real-world applications. Since drivers' physiological indicators (e.g., heart rate) have been reported to change over time in automated vehicles (de Winter et al., 2014; Heikoop et al., 2017), we also investigate the differences in driver's SA and mental stress over time (i.e., successive takeover situation experiences) using their corresponding physiological indicators. In addition, we analyze the correlations between these physiological indicators to investigate the relationship between driver's SA and mental stress.

Takeover performance is typically modeled using driver reaction time (e.g., takeover time) (B. Zhang et al., 2019), driving performance indicators (e.g., minimum time-to-collision and maximum deceleration rate) (Lu et al., 2019; Radlmayr et al., 2014), physical performance (e.g., hands-on-wheel time) (Yoon & Ji, 2019), and visual performance (e.g., time-to-first-gaze) (J. Kim et al., 2018). However, these indicators are often modeled independently, and therefore do not provide a comprehensive understanding of takeover performance. A few recent efforts have been made to propose comprehensive takeover performance metrics (Agrawal & Peeta, 2020; Radlmayr, Ratter, et al., 2018). This study uses the Takeover Performance Index (TOPI) proposed in our previous work (Agrawal & Peeta, 2020) as it provides a single metric to benchmark the effects of driver state on the overall takeover performance (see Section 5.2.5 for details).

Although several studies have evaluated driver state using physiological indicators measured using electrocardiogram (ECG) and eye-tracking instruments as discussed before, few have analyzed their impacts on takeover performance in conditionally automated vehicles. (Zeeb et al., 2015) used on-road glance frequency, on-road glance duration, and maximum eyes-off-road time to classify drivers into low-, medium- and high-risk groups, and analyzed the differences in takeover performance using brake reaction times and percentage of collisions among these groups. Alrefaie et al. (2019) analyzed the impacts of normalized heart rate and normalized pupil diameter on driver's reaction time during the takeover event. They also correlated the physiological indicators with the mean percentage change in the vehicle's speed and heading angle before the takeover event to evaluate the driver's preparedness to respond to the event. A few other studies investigated the differences in physiological indicators under different experimental conditions (e.g., type of takeover warning) in the context of takeover performance, but did not directly analyze their impacts on takeover performance (Lu et al., 2019; Petersen et al., 2019). A key drawback of the aforementioned studies is that they do not capture the impacts of physiological indicators on the overall takeover performance, as they model multiple takeover performance measures independently. Our study benchmarks the impacts of ECG and eye-tracking-based measures on the overall takeover performance using the TOPI. Since these measures can be obtained via in-vehicle driver monitoring systems, this will provide valuable insights to auto manufacturers for developing integrated in-vehicle driver monitoring and warning systems that can enhance road safety.

This study designs driving simulator experiments to evaluate takeover performance in conditionally automated vehicles. Using these experiments, it estimates driver state (i.e., SA and mental stress) from physiological data (i.e., eye-tracking and heart rate measures) that in the real world can be measured using in-vehicle driver monitoring systems. The study also analyzes the differences in driver state over time (i.e., successive takeover situation experiences through multiple experiment runs). Further, it explores the correlations between the physiological indicators of SA and mental stress, and analyzes their overall impacts on takeover performance. Hereafter, we use the term "physiological indicators" to refer to the four eye-tracking and heart rate measures used in this study: on-road glance rate during the automated driving, road attention ratio during the automated driving, pre-warning normalized heart rate, and the change in normalized heart rate after the takeover warning.

The study contributions are as follows. First, most studies either do not analyze the impacts of driver state on takeover performance or consider them indirectly through experimental manipulation. Some studies analyze these impacts directly, but use physiological data (EEG) that is not suited for real-world applications. We estimate driver's SA and mental stress using eye-tracking and heart rate measures that can be measured using in-vehicle driver monitoring systems, and therefore, can be deployed in practice. Second, unlike previous studies that model takeover performance using multiple indicators independently, we benchmark the effects of the driver state on takeover performance using a comprehensive metric (TOPI) that provides an overall assessment of the takeover performance.

The remainder of the paper is organized as follows. Section 5.2 outlines the experiment design and data collection procedures. Section 5.3 discusses the statistical analysis methods used to evaluate the differences in driver's SA and mental stress over time, and their impacts on takeover performance. Section 5.4 presents the analysis results and summarizes the study findings. Section 5.5 concludes the paper by summarizing the study contributions and providing some future research directions.

5.2 Methodology

5.2.1 Apparatus

5.2.1.1 Driving simulator

The study experiments were conducted using a medium-fidelity driving simulator (AVSimulation, 2020), as shown in Figure 5.1. The simulator features a full-scale driving cockpit and a steering wheel with force feedback. The driving view was projected on three LCD screens with a 120 degrees field-of-view. Side-view mirrors, rear-view mirror, and speedometer were presented on the screens. A four-lane divided highway with a medium level of ambient traffic (about 6-7 vehicles in a 500-meter radius) and a speed limit of 105 kph (about 65 mph) was created using the SCANeRStudio® 1.7 software. Since a straight road could artificially reduce the driver's mental stress to monitor the driving environment and potentially enhance SA, the highway was deliberately chosen to replicate the road curvatures of sections of the U.S. Interstate 65 between West Lafayette, IN and Chicago, IL. Driving data was collected at 20 Hz frequency.

Figure 5.1 Driving simulator and non-driving related task

5.2.1.2 Automated driving system

The automated driving system (ADS) implemented in this study mimicked a conditionally automated vehicle that could perform both longitudinal and lateral control on the highway. It was set to observe the speed limit and stay in the right-most lane unless it had to pass a slower moving vehicle in the lane. Drivers could activate the ADS by pulling the indicator stalk on the left of the steering wheel while driving in the middle of a lane, and disengage it by either braking or steering at any time. A green icon with the alphabet "A" on the rear-view mirror indicated that the ADS was active.

The ADS provided two types of takeover warnings: an uncertainty alert and a takeover request (TOR). An uncertainty alert (presented as a single auditory chime) denoted that the system is unsure of its ability to drive safely and prompted for driver's attention to the road without the need for manual intervention (non-mandatory takeover). In contrast, a TOR (presented as three auditory chimes in quick succession) denoted a system failure and required immediate driver intervention (mandatory takeover). In this study, a TOR was always preceded by an uncertainty alert. The warnings were delivered via two multimedia speakers positioned on each side of the driving cockpit below the screens.

5.2.1.3 Non-driving related task (NDRT)

During the automated drive, participants were asked to engage in an NDRT that consisted of a repetitive number transcription task. The NDRT was delivered on a touchscreen tablet that was positioned near the center console (see Figure 5.1). The participants completed a single task by inputting two six-digit numbers and a mathematical operator shown on the left side of the tablet screen into a calculator interface and pressing “submit” when done. This simulated visual-motor distraction for the participants. Numeric characters were chosen over alphanumeric characters to avoid potential language-specific biases.

5.2.1.4 Electrocardiogram (ECG)

Participants’ heart electrical activities were recorded during the simulated runs using the B-Alert X-24 EEG and ECG systems (Advanced Brain Monitoring, 2017). The ECG recorded electrical signals at a sampling rate of 256 Hz using four electrodes: one at the right collar bone, one at the lowest left rib, and two at the mastoids (reference for measuring the power of the signal). We used the B-Alert software to extract heart rate (HR) using the electrical signals at 1-second intervals (B-Alert, 2009).

5.2.1.5 Eye-tracking glasses

Wearable eye-tracking glasses, Dikablis Glasses 3 (Ergoneers, 2018), were used to collect participants’ eye gaze patterns. Its design allows it to be equipped on top of participants’ corrective glasses, if needed, without affecting measurements. We defined a road area-of-interest (AOI) in the DLAB software (Ergoneers, 2018) by attaching QR code tags on the corners of the three simulator screens to compute two eye-tracking statistics related to the road monitoring behavior: on-road glance rate (OGR; number of glances at the road AOI per unit time) and road attention ratio (RAR; percentage of time spent glancing at the road AOI).

5.2.2 Experiment design

The study experiments were designed as a part of a larger study that investigates the effects of introductory information on driver’s trust in automation and takeover performance. The study participants were divided into two groups based on the content of the introduction video that they viewed. However, our study disregards this grouping as no statistically significant differences were found in the takeover performance between the two groups (see Souders et al., 2020 for details).

Participants completed three experiment runs (approximately 10, 10, and 7 minutes, respectively) with moderate ambient traffic density. Each run culminated in a different safety-critical event that was preceded by a takeover warning, as described in Table 5.1. Since the larger study focuses on driver's trust in automation that can change with prior experiences, the order of the runs was not randomized to control the order of the takeover experiences for the participants.

Table 5.1 Safety-critical event details

Run	**Time budget for takeover warning**		**Safety-critical event description**
	Uncertainty alert	Takeover request	
1	6 seconds	-	Lateral automation late to change lane (2-second time budget), resulting in a close pass of a slower moving bus (35 kph)
2	8 seconds	4 seconds	A broken-down vehicle (0 kph) occluded by a slower moving bus (35 kph) blocking the lane
3	7 seconds	-	Longitudinal automation late to apply brakes (3-second time budget) for a slower moving bus (55 kph)

5.2.3 Procedure

Before arriving at the lab for the driving simulator experiments, participants completed an online survey designed to check their participation eligibility (see Section 5.2.6 for the eligibility criteria) and to gather their sociodemographic and other behavioral/attitudinal details (see Souders et al., 2020 for details). Eligible participants were directed to a website for scheduling a driving simulator session. During the lab visit, participants signed an informed consent form and were introduced to the complete experiment procedure. Then, they completed a practice run in the simulator that involved manually driving the simulated vehicle in an urban environment. This run was designed to acclimatize them with the simulator and to serve as a screening procedure for participants with simulator sickness. Next, participants viewed the introductory video for their randomly assigned group. A double-blind manipulation, where neither the experimenter nor the participant knew about the assigned group, was implemented. Then, participants were equipped with the eye-tracker and the EEG and ECG instruments. This study does not analyze EEG data; please see Agrawal and Peeta (2020) for the detailed EEG related analysis. Next, participants completed another practice run with the ADS and NDRT concurrently on a four-lane divided highway to get acquainted with the ADS's activation/deactivation procedures and takeover warnings. There was no ambient traffic in the practice run, except for the three slower-moving vehicles that were used initially to illustrate the capabilities of the ADS to pass them. Traffic cones were used as obstacles to simulate potential takeover events that trigger the issuance of a takeover warning. In addition, each takeover warning was preceded by a voice message (i.e., "pay attention to the road" for an uncertainty alert, and "take over manual control" for a TOR) to prepare the participants for the event. The practice run continued until the participants verbally confirmed that they are comfortable with handling the ADS. Following the practice run, participants completed three experiment runs. They were instructed to keep the ADS activated throughout the run unless they are concerned about road safety. In conditionally automated driving, it is expected that drivers would disengage from driving and engage in other NDRTs. Thus, to promote such behavior, participants were informed that their final compensation for participation would depend on the number of correct responses to the NDRT as well as road safety across all three runs. Regardless, all participants received full compensation of $45 at the end of the experiment. Participants also completed a few surveys between runs and after the three runs (see Souders et al., 2020 for details). Our study does not use data collected from these surveys. Finally, they were debriefed and compensated for their participation. The experiment protocol was approved by the Purdue University's Institutional Review Board (protocol #1811021326).

5.2.4 Data preprocessing

Since the base HR differs across individuals, HR were normalized for each participant to alleviate the individual differences. The normalized heart rate (NHR) for each individual is computed using Eq. (5.1), where HR_t is the heart rate at time step t, and $\mathrm{HR}_{\mathrm{min}}$ and $\mathrm{HR}_{\mathrm{max}}$ are the minimum and maximum heart rates, respectively, over all three runs.

$$\mathrm{NHR} = \frac{\mathrm{HR}_t - \mathrm{HR}_{\mathrm{min}}}{\mathrm{HR}_{\mathrm{max}} - \mathrm{HR}_{\mathrm{min}}} \tag{5.1}$$

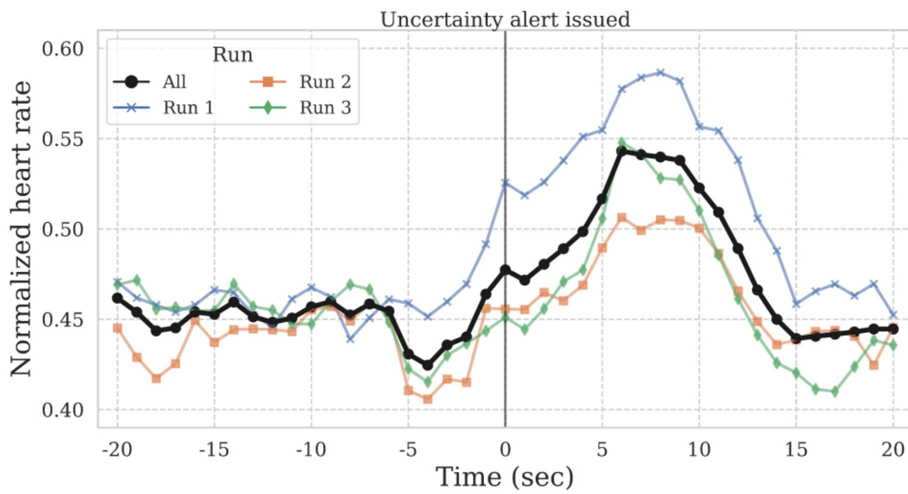

Figure 5.2 Normalized heart rates before and after the uncertainty alert

Figure 5.2 shows the NHRs before and after the uncertainty alert for all three runs and their average. Pre-warning NHR (pre-NHR) and post-warning NHR (post-NHR) are computed by averaging the NHR for 15-second time windows before and after the issuance of the uncertainty alert, respectively. A 15-second time window was chosen to match the time window for the driving data used to compute the TOPI (see Section 5.2.5). The change in NHR (ΔNHR) due to the takeover warning was calculated as the difference between post-NHR and pre-NHR. We use pre-NHR to assess driver's pre-warning mental stress and ΔNHR to assess the change in mental stress after the takeover warning. Figure 5.2 illustrates that the NHR after the warning increases for about 6 to 8 seconds, which is similar to the time budget for the uncertainty alert used in this experiment (see Table 5.1), and then returns to normal in about 15 seconds from the uncertainty alert. This is most likely due to the increase in mental stress as participants approach the blocking vehicle, which starts reducing (for most participants) after they have successfully maneuvered around the blocking vehicle. Further, the figure shows that the NHR after the warning is higher in run 1 compared to the other two runs. This suggests that the participants experienced higher mental stress in the first run that decreased in the later runs, most likely because they became more comfortable with the driving simulator and the overall experiment setup as the experiment progressed. However, the change in NHR is similar in all three runs, which indicates that the increase in mental stress from the takeover event does not change with prior experiences.

The eye-tracking measures (OGR and RAR) for each run are computed from the beginning of each run until 10 seconds before the issuance of the uncertainty alert. A 10-second time window is chosen to have as little gap as possible before the safety-critical events' vehicle(s) visibly respond to execute the event. Time intervals during which the participant disengaged the ADS (i.e., manual driving) were excluded while computing these measures. We use these measures to assess driver's SA during the automated driving before the takeover event.

5.2.5 Takeover performance metric

This study uses the comprehensive takeover performance metric, Takeover Performance Index (TOPI), proposed in our previous work (Agrawal & Peeta, 2020). Unlike other takeover performance metrics (e.g., Radlmayr, Ratter, et al., 2018), the TOPI captures the interdependencies between different driving indicators and provides a single metric to evaluate the overall takeover performance; thereby enabling us to benchmark the effects of driver state (i.e., SA and mental stress) and other factors (i.e., novelty in takeover experience and type of takeover warning) on takeover performance. Since the current study and our previous study (Agrawal & Peeta, 2020) use data from the same experiments, we use the same driving performance indicators (i.e., minimum time-to-collision, maximum deceleration, maximum steering wheel angle, and maximum lateral trajectory deviation) and their corresponding parameter values to compute the TOPI value. We use driving data collected within a 15-second time window after the issuance of the uncertainty alert to compute driving performance indicators for the TOPI. Further, the TOPI is not calculated for runs in which participants took over vehicle control before an uncertainty alert was issued.

5.2.6 Participants

Participants were recruited from the Greater Lafayette community in Indiana, through advertisements in the Purdue University's weekly email newsletter, paper fliers at community events, and word of mouth. Participant eligibility criteria included: (i) being 18 years of age or older, (ii) having a valid driver's license, (iii) having no predisposition to motion sickness, (iv) self-reporting the absence of any mental impairments or physical impairments that would make it difficult for them to get in and out of the simulator unassisted, and (v) passing an over-the-phone memory impairment test (Wechsler Logical Memory Scale; Wechsler, 1997) if over the age of 64 years. In addition, participants were asked to avoid consuming any medication or caffeine for at least 8 hours prior to the driving simulator experiment session (see Agrawal & Peeta, 2020 for details).

Overall, 134 drivers participated in this study, yielding a total of 402 experiment runs. Of these, participants took manual control of the vehicle after a takeover warning was issued in 340 runs. 19 runs were excluded from the analysis due to an unexpected error (a rouge vehicle appearing in front of the ego vehicle) during the takeover event, resulting in a total of 321 runs for 131 participants with valid TOPI values. Figure 5.3 shows the age (28.9 ± 13.8 years) and gender (68 females and 63 males) distribution of the participants for these runs. Further, data was filtered to exclude runs with invalid eye-tracking (OGR and RAR) and heart rate measures (pre-NHR and ΔNHR) from their corresponding analysis (see Section 5.4.1). The invalid physiological data was due to two possible reasons: (i) eye-tracker or ECG equipment malfunctioned resulting in their corresponding missing or poor-quality data, and (ii) problems in synchronizing the physiological data with the driving data due to missing timestamps. Table 5.2 presents the valid data counts for the TOPI, pre-NHR, ΔNHR, OGR, RAR, and their combinations.

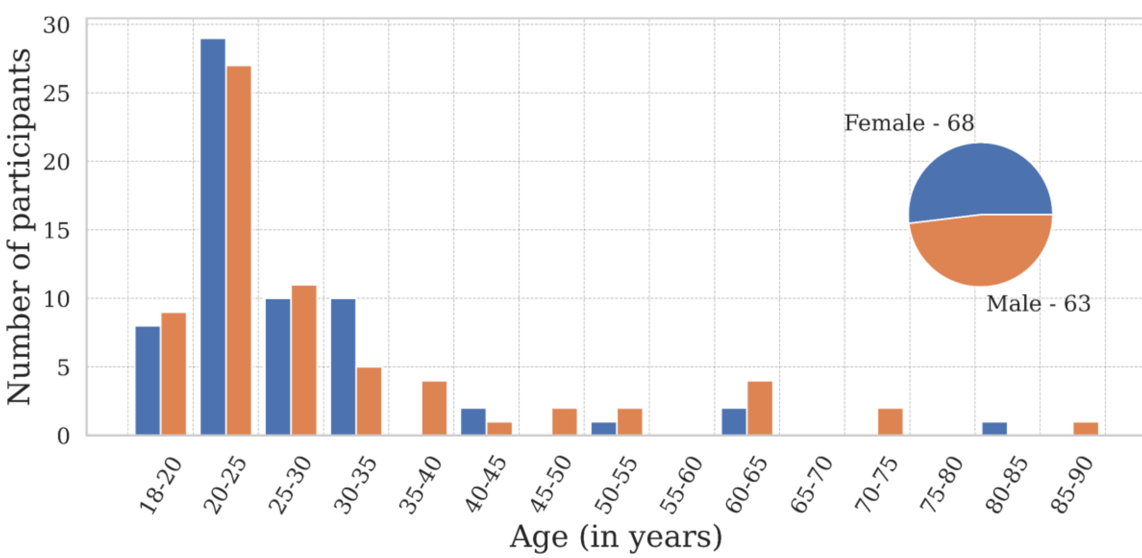

Figure 5.3 Age and gender distribution of the participants

Table 5.2 Valid data counts for the TOPI and physiological indicators

Measures						Valid counts
TOPI	Pre-NHR	ΔNHR	OGR	RAR	Runs	Participants
✓					321	131
	✓				250	103
		✓			227	100
✓	✓				216	102
✓	✓	✓			193	99
			✓	✓	219	79
✓			✓	✓	194	79
✓	✓		✓	✓	128	62
✓	✓	✓	✓	✓	114	60
Note: ✓ denotes valid data for the corresponding measures						

5.3 Statistical analyses

As stated earlier, the study investigates the differences in driver's SA and mental stress over time (i.e., successive experiment runs) and their impacts on takeover performance in conditionally automated vehicles. To do so, we use the following physiological measures as indicators of driver state: OGR and RAR for SA during the automated driving, pre-NHR for pre-warning mental stress, and ΔNHR for change in mental stress after the takeover warning. We use the TOPI to benchmark the effects of driver state on the overall takeover performance. In addition, we analyze the impacts of other factors, including novelty in takeover experience (i.e., indicator variable for the first run) and type of takeover warning (uncertainty alert and TOR), on takeover performance using the TOPI. We also analyze the correlations between these physiological indicators to investigate the relationship between SA and mental stress in conditionally automated vehicles.

We estimate linear mixed models (LMMs) to analyze the differences in physiological indicators over successive experiment runs. LMM is used for two key reasons: (i) it accounts for the correlated errors that arise due to panel data (multiple runs from the same participant) by modeling them as random effects, and (ii) it provides unbiased results without the need to exclude the entire data (all three runs) for a participant if a single data point (single run) is missing or invalid. Therefore, it enables us to use data for participants who did not take over manual control of the vehicle (i.e., TOPI is not calculated) or did not have valid physiological data in all three runs (see Table 5.2).

In this study, we estimate 8 LMMs, four to analyze the differences in each physiological indicator over successive runs and another four to analyze the effect of each physiological indicator on the TOPI. The reason for analyzing the impacts of physiological indicators on the TOPI separately is the loss of data for combinations of physiological indicators (see Table 5.2). The basic form of the estimated LMMs to analyze the differences in physiological indicators is given by Eq. (5.2) and to analyze their impacts on the TOPI is given by Eq. (5.3).

$$\mathrm{PI} = \beta_0 + \beta_{\mathrm{run}} + \gamma + \varepsilon \tag{5.2}$$

$$(\mathrm{TOPI})^2 \sim \beta_0 + \beta_{\mathrm{PI}} + \beta_{\mathrm{nov}} + \beta_{\mathrm{TOR}} + \gamma + \varepsilon \tag{5.3}$$

In Eq. (5.2), PI denotes the physiological indicator and is the dependent variable for the corresponding analysis. We analyze the differences in the physiological indicators over time by using a discrete variable for experiment runs represented by β_{run}. We treat β_{run} as a discrete variable instead of a continuous variable to avoid assuming that the differences in physiological indicators over time are linear. In Eq. (5.3), $(\mathrm{TOPI})^2$ denotes the square of the TOPI value and is the dependent variable. We transform (squared) TOPI to meet the model assumption of normality of residuals. β_{PI}, β_{nov}, and β_{TOR} denote the effect of the physiological indicator PI, novelty in takeover experience (indicator variable for the first run), and the presence of TOR, respectively. In both equations, β_0, γ, and ε denote the model intercept, random effects coefficient for the panel data, and normally distributed error term, respectively.

In our previous study (Agrawal & Peeta, 2020), we found a strong positive stepwise trend in driver's takeover performance due to learning effects after their first experience with a takeover situation (i.e., novelty effects). We also reported a strong negative effect of the presence of TOR on takeover performance in the same study. Thus, we model these effects as covariates in the current study to accurately benchmark the effects of physiological indicators on takeover performance.

A likelihood-ratio test (LRT) is used to assess the goodness-of-fit of each LMM with its corresponding null model (i.e., linear model without the random effects). If the LRT does not indicate a better goodness-of-fit of the LMM compared to its null model, the linear model is used to analyze the corresponding effects. The model assumption of normality of residuals is tested using the Shapiro-Wilk test, which tests the null hypothesis that the data is normally distributed. If the null hypothesis is rejected (i.e., $p < 0.05$), a visual inspection using a quantile-quantile (QQ) plot is performed to determine normality of the residuals. Further, the statistical significance of differences in the physiological indicators over experiment runs is tested using ANOVA for the estimated LMMs. Satterthwaite's formula is used to approximate the effective degrees-of-freedom to account for different sample variances in ANOVA. Post-hoc multiple comparison Tukey's test with Holm-Bonferroni correction for family-wise error rate is also performed to pairwise compare these differences between runs. The correlations between the physiological indicators are estimated using repeated measures correlation analysis to account for the panel data (Bakdash & Marusich, 2017).

5.4 Results

5.4.1 Physiological indicators

This section discusses the results of the estimated LMMs and post-hoc analyses to evaluate the differences in driver's SA and mental stress over successive experiment runs using physiological indicators. It also analyzes the correlations between these physiological indicators.

5.4.1.1 On-road glance rate

The model estimation results for differences in OGR over runs are presented in Table 5.3. A likelihood-ratio test ($\chi^2(1) = 84.41, p < 0.001$) illustrates a significantly better goodness-of-fit of the LMM ($N = 219,$ groups $= 79$) compared to its corresponding null model. Model results show significant differences in OGR for different runs ($F(2, 142.7) = 16.241, p < 0.001$). A multiple comparison Tukey's test indicates that OGR is significantly higher in Run 1 compared to Run 2 and Run 3. This suggests that the drivers monitored the road more frequently in the first run, which could be attributed to their first real experience with the ADS in the driving simulator. In this context, while they practiced driving with the ADS in the practice run, it was in a simplified driving environment with no traffic (see details in Section 5.2.3). However, no significant differences in OGR were found between Run 1 and Run 2, indicating that drivers were quick to adapt the frequency of on-road glances that they believe is sufficient to maintain their desired levels of SA. The model did not satisfy the assumption of normality of residuals using the Shapiro-

Wilk test ($W = 0.791, p < 0.001$). However, a visual inspection of the QQ plot suggests that the residuals are normally distributed.

Table 5.3 Model results for on-road glance rate (OGR)

	Parameter	Estimate/Value	Std. Error	DF	Sig.
Data	N	219			
	Groups	79			
Fixed Effects	Intercept	0.122^{***}	0.009	78.6	< 0.001
	Run 1	0.029^{***}	0.005	143.2	< 0.001
	Run 2	-0.008	0.005	143.3	0.113
Random Effects	Group variance	0.005			
	LRT (χ^2)	84.41^{***}		1	< 0.001
ANOVA	Run (F)	16.241^{***}		(2, 142.7)	< 0.001
Multiple Comparison Tukey's test	Run 2 – Run 1	-0.038^{***}	0.009		< 0.001
	Run 3 – Run 1	-0.050^{***}	0.009		< 0.001
	Run 3 – Run 2	-0.013	0.009		0.165
Model Assumption	Shapiro-Wilk test (W)	0.791^{***}			< 0.001
Note: *** p < 0.01; ** p < 0.05; * p < 0.1					

5.4.1.2 Road attention ratio

The model estimation results for differences in RAR over runs are presented in Table 5.4. A likelihood-ratio test ($\chi^2(1) = 123.44, p < 0.001$) illustrates a significantly better goodness-of-fit of the LMM ($N = 219$, groups $= 79$) compared to its corresponding null model. LMM results show significant differences in RAR for different runs ($F(2, 141.5) = 24.175, p < 0.001$). A multiple comparison Tukey's test indicates that RAR is significantly higher in Run 1 compared to Run 2 and Run 3. No significant differences in RAR were found between Run 2 and Run 3. Similar to OGR, this suggests that drivers monitored the road for longer duration, on average, in the first run, but were quick to adapt their road monitoring behavior to maintain their desired levels of SA. The model did not satisfy the assumption of normality of residuals using the Shapiro-Wilk test ($W = 0.982, p = 0.006$). However, a visual inspection of the QQ plot suggests that the residuals are normally distributed.

Table 5.4 Model results for road attention ratio (RAR)

	Parameter	Estimate/Value	Std. Error	DF	Sig.
Data	N	219			
	Groups	79			
Fixed Effects	Intercept	13.459***	0.977	78.3	< 0.001
	Run 1	3.194***	0.471	141.9	< 0.001
	Run 2	-1.006**	0.466	142.0	0.033
Random Effects	Group variance	66.710			
	LRT (χ^2)	123.44***		1	< 0.001
ANOVA	Run (F)	24.175***		(2, 141.5)	< 0.001
Multiple Comparison Tukey's test	Run 2 – Run 1	-4.200***	0.815		< 0.001
	Run 3 – Run 1	-5.383***	0.809		< 0.001
	Run 3 – Run 2	-1.183	0.800		0.139
Model Assumption	Shapiro-Wilk test (W)	0.982***			0.006
Note: *** p < 0.01; ** p < 0.05; * p < 0.1					

5.4.1.3 Pre-warning heart rate

The model estimation results for differences in pre-NHR over runs are presented in Table 5.5. A likelihood-ratio test ($\chi^2(1) = 76.09, p < 0.001$) illustrates a significantly better goodness-of-fit of the LMM ($N = 250$, groups $= 103$) compared to its corresponding null model. Model results show marginally significant differences in pre-NHR for different runs ($F(2, 155.1) = 2.928, p = 0.056$). A multiple comparison Tukey's test indicates that pre-NHR is marginally higher in Run 1 compared to Run 2. However, no statistically significant differences were found between Run 3 and the other runs. This suggests that drivers experienced significantly higher mental stress in the first run before the takeover warning. This is consistent with other driving simulator studies that have reported a decrease in heart rate due to driving stress as the experiment progresses (time-on-task effects). It happens because the participants become more comfortable with the experiment setup over time. However, we only observe a weaker time-on-task effect as the pre-NHR is higher, although not significantly, in Run 3 compared to Run 2. This could be due to the fixed order of runs where drivers encountered a mandatory takeover situation in the second run, which may have affected their level of stress going forward. The model did not satisfy the assumption of normality of residuals using the Shapiro-Wilk test ($W = 0.976, p < 0.001$). However, a visual inspection of the QQ plot suggests that the residuals are normally distributed.

Table 5.5 Model results for pre-warning normalized heart rate (pre-NHR)

	Parameter	Estimate/Value	Std. Error	DF	Sig.
Data	N	250			
	Groups	103			
Fixed Effects	Intercept	0.457***	0.012	98.7	< 0.001
	Run 1	0.019**	0.008	156.4	0.022
	Run 2	-0.014*	0.008	154.0	0.073
Random Effects	Group variance	0.012			
	LRT (χ^2)	76.09***		1	< 0.001
ANOVA	Run (F)	2.928*		(2, 155.1)	0.056
Multiple Comparison Tukey's test	Run 2 – Run 1	-0.033*	0.014		0.053
	Run 3 – Run 1	-0.023	0.014		0.194
	Run 3 – Run 2	0.010	0.014		0.471
Model Assumption	Shapiro-Wilk test (W)	0.976***			< 0.001
Note: *** p < 0.01; ** p < 0.05; * p < 0.1					

5.4.1.4 Change in heart rate

The model estimation results for differences in ΔNHR over runs are presented in Table 5.6. A likelihood-ratio test ($\chi^2(1) = 42.57, p < 0.001$) illustrates a significantly better goodness-of-fit of the LMM ($N = 227,$ groups $= 100$) compared to its corresponding null model. Model results did not show any statistically significant differences in ΔNHR across runs ($F(2, 147.0) = 1.147$, $p = 0.320$); thus, a post-hoc multiple comparison Tukey's test is not performed. The results indicate that drivers experienced a similar increase in mental stress during the takeover event across all three runs. This suggests that drivers' prior experiences with takeover events may not affect the increase in stress levels, which could have negative implications for road safety and drivers' trust in the ADS. However, these results may be valid only in the short-term as we only used three experiment runs, and therefore, further research is needed to examine the long-term effects. The model did not satisfy the assumption of normality of residuals using the Shapiro-Wilk test ($W = 0.987, p = 0.039$). However, a visual inspection of the QQ plot suggests that the residuals are normally distributed.

Table 5.6 Model results for change in normalized heart rate (**Δ**NHR)

	Parameter	Estimate/Value	Std. Error	DF	Sig.
Data	N	227			
	Groups	100			
Fixed Effects	Intercept	0.045^{***}	0.012	99.8	< 0.001
	Run 1	0.015	0.010	147.8	0.134
	Run 2	-0.005	0.010	147.2	0.542
Random Effects	Group variance	0.009			
	LRT (χ^2)	42.57^{***}		1	< 0.001
ANOVA	Run (F)	1.147		(2, 147.0)	0.320
Model Assumption	Shapiro-Wilk test (W)	0.987^{**}			0.039
Note: *** p < 0.01; ** p < 0.05; * p < 0.1					

Table 5.7 Repeated measures correlation matrix for physiological indicators

Indicators	OGR	RAR	pre-NHR	ΔNHR
OGR	-			
RAR	0.498 (139, < 0.001***)	-		
pre-NHR	0.023 (84, 0.831)	0.079 (84, 0.469)	-	
ΔNHR	-0.125 (72, 0.288)	-0.010 (72, 0.936)	-0.487 (126, < 0.001***)	-
Note: Degrees of freedom and p-value are shown in parentheses *** p < 0.01; ** p < 0.05; * p < 0.1				

5.4.1.5 Correlation analysis

The estimated repeated measures correlations between the physiological indicators are presented in Table 5.6. We found a strong positive correlation between OGR and RAR, which is expected as both of them are indicators of driver's SA from monitoring of the road. We also found a strong negative correlation between pre-NHR and ΔNHR, which can be attributed to their functional relationship. However, we did not find any statistically significant correlations between eye-tracking measures (OGR and RAR) and heart rate measures (pre-NHR and ΔNHR). This suggests that driver's SA during automated driving may not affect their mental stress significantly in conditionally automated vehicles. It also illustrates the need for considering multiple sources of physiological data in in-vehicle driver monitoring systems to estimate a detailed profile of the driver state.

5.4.2 Takeover performance

The effect of ΔNHR ($F(1, 160.8) = 5.964$, $p = 0.016$) on the TOPI was found to be statistically significant. However, a likelihood-ratio test ($\chi^2(1) = 1.659$, $p = 0.198$) shows that the LMM ($N = 193$, groups $= 99$) did not have a better goodness-of-fit compared to its corresponding null model. Thus, takeover performance is evaluated using a linear model with no random effects. The model results of the estimated linear model are presented in Table 5.8. An adjusted R-squared value of 0.281 indicates a good model fit. Model results show significant negative effects of the novelty in takeover experience ($F(1, 189) = 70.320$, $p < 0.001$) and the presence of TOR ($F(1, 189) = 21.950$, $p < 0.001$) on the TOPI. These results are consistent with the findings of our previous work that discussed their effects in detail (Agrawal & Peeta, 2020). The results also indicate a significant negative effect of ΔNHR on the TOPI ($F(1, 189) = 3.946$, $p = 0.048$). This suggests that the change in driver's heart rate after the takeover warning significantly affects their takeover performance. Previous studies have linked an increase in heart rate with the surprise emotion in unexpected events (Jang et al., 2015) and with an increase in task-induced mental stress (Alrefaie et al., 2019). In our context, the unexpected event is the takeover situation, and the task is taking over vehicle control. Past studies have also shown that the effects of mental stress on decision-making and performance are task-specific (Starcke & Brand, 2012). This suggests that the increase in stress (i.e., higher ΔNHR) during a takeover event may have led to poor instantaneous decision-making by drivers resulting in in poor takeover performance. However, it should be noted that the increase in stress after the takeover warning may have a bi-directional relationship with takeover performance, as inadequate or improper driving responses during a rapidly evolving takeover situation could cause more stress to the driver. The estimated linear model met the assumption of normality of residuals using the Shapiro-Wilk test ($W = 0.990$, $p = 0.194$).

The effects of OGR ($F(1, 122.9) = 0.052$, $p = 0.820$), RAR ($F(1, 122.1) = 0.354$, $p = 0.553$), and pre-NHR ($F(1, 179.1) = 0.172$, $p = 0.679$) on the TOPI were not found to be statistically significant. These results suggest that the driver's SA during automated driving and their level of stress before the takeover warning do not have significant impact on takeover performance. This is interesting as previous studies have suggested that increasing driver's SA could improve their takeover performance (Olaverri-Monreal et al., 2018; Petersen et al., 2019). There are two possible explanations for this. First, those studies do not use a comprehensive takeover performance metric and, thereby, observed improvements in only some aspects of the takeover performance (e.g., reaction times) but not the overall takeover performance. Second, our study participants maintained a sufficient level of SA, and hence it did not significantly affect their takeover performance.

Table 5.8 Model results for the effects of **Δ**NHR on the TOPI

	Parameter	Estimate/Value	Std. Error	DF	Sig.
Data	N	193			
Fixed Effects	Intercept	0.393***	0.016		< 0.001
	Novelty	-0.214***	0.025		< 0.001
	TOR	-0.119***	0.025		< 0.001
	ΔNHR	-0.150*	0.075		0.048
Model	Model fit (F)	26.030***		(3, 189)	< 0.001
	Adjusted R-squared	0.281			
Model Assumption	Shapiro-Wilk test (W)	0.990			0.194

Novelty: Novelty in takeover experience
TOR: Presence of TOR
Note: *** p < 0.01; ** p < 0.05; * p < 0.1

5.4.3 Summary of findings

The study results show a significantly higher SA in the first run compared to the later runs, measured by eye-tracking indicators (i.e., OGR and RAR), as illustrated in Table 5.3 and Table 5.4. However, it was not found to be significantly different among the later runs. This suggests that drivers initially expended more visual resources to scan the road environment, most likely due to the novelty in the automated driving experience, but were quick to adjust their road monitoring behavior to maintain a level of SA during the automated driving that they deemed to be sufficient. A key advantage of driver monitoring systems is that they can track driver state in real-time, which the vehicle can use to alert the driver or take certain maneuvering actions. In this context, the study insights have key implications for auto manufacturers and driver monitoring system designers to determine the optimal level of the driver's SA using eye-tracking measures that enhances user experience by reducing false alarms in conditionally automated vehicles.

Previous studies have reported that the driver's heart rate reduces over time in partially automated vehicles (Heikoop et al., 2017, 2018). This decline in the heart rate is attributed to a decrease in mental stress, and an increase in passive fatigue and mental underload during automated driving. However, our results show only a marginal decrease in pre-NHR, as illustrated in Table 5.5. This suggests that the heart rate and, thereby, mental stress may not reduce significantly over time under conditional automation. However, since we did not compare between driving in partially automated vehicles and conditionally automated vehicles, it is possible that the heart rate is initially lower (i.e., lower mental stress) under conditional automation. In addition, we did not find significant differences in ΔNHR between runs (see Table 5.6). This suggests that the time spent in automated driving as well as the number of takeover experiences may not affect the change in driver's mental stress during an unexpected takeover situation. These insights can aid policymakers to develop operator training programs that focus on mental stress management during takeover situations so as to enhance driver's trust in conditionally automated vehicles and promote their adoption. Auto manufacturers can also use these insights to design takeover warning systems that reduce the increase in driver's mental stress during a takeover event to alleviate the negative impacts of bad experiences (e.g., takeover events) on driver's trust and user experience.

The lack of correlations between eye-tracking measures and heart rate measures indicates that the level of SA during the automated driving does not have significant impact on driver's pre-warning mental stress or the change in mental stress after the takeover warning. These insights suggest that driver monitoring system designers should consider using different sources of physiological data to assess the driver state as a single source may not be sufficient to estimate different aspects of the driver state.

The results also illustrate a significant negative effect of ΔNHR on the TOPI. This suggests that unexpected takeover events that require immediate safety-critical responses from drivers increase their mental stress, which could further lead to poor instantaneous decision-making while taking control of the vehicle from the ADS. In addition, a bi-directional relationship is possible whereby improper driving responses lead to a more dangerous situation that increases driver's mental stress. Future studies can investigate this potential bi-directional relationship between the increase in stress and takeover performance. Further, as discussed earlier, we did not find any significant differences in ΔNHR over time (successive experiment runs). This indicates that prior experiences with takeover situations may not affect the change in driver's mental stress during an unexpected takeover situation over time, implying that learning from prior takeover experiences may be overshadowed by the surprise factor with the unexpected event. These insights suggest that it may be useful for auto manufacturers to monitor the changes in driver's mental stress during takeover situations through driver monitoring systems, and adjust the ADS and takeover warning system parameters to reduce mental stress increase to enhance user experience and road safety.

In line with our previous work (Agrawal & Peeta, 2020), the results illustrate significant negative impacts of novelty in takeover experience and the presence of TOR, on takeover performance. These have key implications for policymakers to develop operator training and driver licensing strategies as well as for auto manufacturers to design fallback procedures, as discussed in our previous work.

We did not find significant impacts of driver's SA during the automated driving (OGR and RAR) and pre-warning mental stress (pre-NHR) on their takeover performance. This suggests that the driver's SA did not significantly impact their takeover performance under conditional automation in this study. However, we did not manipulate SA in this study, and hence the lack of significant effects of SA may be because the drivers maintained a sufficient level of SA that is needed in conditionally automated vehicles. The lack of significant effects of pre-warning mental stress on the TOPI is consistent with the findings in our previous work that analyzed the effects of driver's pre-warning cognitive state on the TOPI using EEG indicators (Agrawal & Peeta, 2020). However, in our previous study, we did find the effects of certain pre-warning cognitive states like fatigue, drowsiness, passive attention, and low alertness on the TOPI. Although eye-tracking and heart rate measures do not provide a very detailed profile of the driver state that EEG-based measures would, unlike EEG they can be measured using in-vehicle driver monitoring systems and have real-world applications.

5.5 Concluding Comments

This study analyzes the differences in driver state (in terms of SA and mental stress) over time and their impacts on takeover performance using driving simulator experiments. Driver's SA and mental stress are estimated using physiological indicators that can be measured by in-vehicle driver monitoring systems in the real world. Although these indicators do not provide a detailed profile of driver state, they can be used by auto manufacturers to adjust the ADS and takeover warning system parameters based on the driver state to enhance road safety and user experience.

The study results show that drivers quickly adjust their road monitoring behavior, and consequently their SA after the first automated driving experience. They also show that drivers experience a similar increase in mental stress during a takeover event over time, which becomes a critical issue from the road safety perspective as a higher increase in mental stress results in reduced takeover performance. Thus, the results illustrate the importance of considering driver state characteristics such as mental stress in conditionally automated vehicles to evaluate driver's takeover performance and take appropriate actions in real-time to enhance road safety, by leveraging in-vehicle driver monitoring systems. The study findings provide valuable insights to auto manufacturers and policymakers to design integrated in-vehicle driver monitoring and warning systems, operator training programs, and driver licensing strategies for conditionally automated vehicles, as discussed in the previous section.

The study can be extended in the following ways. First, the study sample is skewed towards younger adults (less than 35 years of age). Further experimentation with a more representative sample of the general population can improve the generalizability of the results. Second, there was a significant data loss due to invalid physiological data. Future efforts can focus on designing data collection protocols more carefully. Third, the order effects of experiment runs were not considered in the analysis. Future studies can randomize the experiment runs to control these studies, which may provide better insights regarding the driver state and takeover performance. Fourth, the effects of NDRT on physiological indicators, especially eye-tracking measures, and their impacts on takeover performance can be explored.

Some potential future directions are as follows. First, other data that can be collected using in-vehicle driver monitoring systems such as skin conductance and facial expressions can be used to augment the eye-tracking and heart rate measures for evaluating takeover performance. Second, future studies can focus on developing integrated in-vehicle driver monitoring and takeover warning systems for conditionally automated vehicles that use the real-time estimation of driver state to predict driver's response in a takeover situation and provide timely and appropriate warnings to prepare them for the approaching road safety hazards.

6. SUMMARY AND CONCLUSIONS

6.1 Research summary

This dissertation systematically investigated the cognitive and psychological aspects of emerging technologies (i.e., real-time travel information systems and conditionally AVs) using physiological data on driver performance and decision-making. It addresses the shortcomings of existing literature that rely on subjective survey-based instruments (i.e., memory biases) to estimate driver cognition by using objective physiological indicators. First, this dissertation analyzed the cognitive and psychological effects induced by real-time travel information systems and their impacts on route choice behavior. Then, it evaluated the impacts of driver's cognitive state on takeover performance in conditionally AVs. Drivers use real-time travel information to make informed medium- to long-term (relative to the duration of a trip) travel decisions, while takeover warnings alert drivers about impending road hazards that require immediate actions. Hence, the cognitive and psychological aspects associated with them vary. This dissertation leverages physiological data to analyze the impacts of cognitive and psychological aspects of these two emerging technologies on driver performance and decision-making. By doing so, it provides a common tool to evaluate the cognitive and psychological aspects of emerging technologies.

Chapters 2 and 3 focused on real-time travel information. Elaborate driving simulator experiments with a network-level setup featuring two routes with different route characteristics (i.e., driving environment complexity) were designed to provide a realistic driving experience and route choice decision-making context under real-time travel information provision. Using the data from these experiments, Chapter 2 evaluated the cognitive and psychological effects of real-time auditory travel information on drivers. EEG band powers were used to estimate the information-induced cognitive and psychological effects by drawing insights from the neuroscience literature. Chapter 3 proposed a hybrid route choice model incorporating the latent information-induced cognitive and psychological effects. Two latent effects, representing the cognitive effort associated with information perception and processing, and the cognitive inattention before implementing the route choice, were estimated using EEG band powers. In addition, the proposed model analyzed the impacts of route characteristics, information characteristics, driver attributes, and situational factors on drivers' cognitive states and route choices.

Chapters 4 and 5 focused on modeling the impacts of driver's cognitive state on takeover performance in conditionally AVs. Driving simulator experiments were designed with an ADS that mimicked a conditionally AV and provided two types of takeover warnings (mandatory and non-mandatory takeover) to analyze the impacts of driver cognition on takeover performance. Chapter 4 analyzed EEG band powers to estimate the driver's pre-warning cognitive state and model its impacts on takeover performance. It also proposed a novel comprehensive takeover performance metric (TOPI) that captures the interdependencies between multiple driving performance indicators to benchmark the effects of driver's pre-warning cognitive state on the overall takeover performance. Although EEG analysis provides a more detailed profile of driver cognition, it is impractical to use it in real-world applications. In this context, Chapter 5 used eye-tracking and heart rate measures that can be obtained from in-vehicle driver monitoring systems to assess driver's SA and mental stress. It analyzed the differences in driver state (in terms of SA and mental stress) over time and their impacts on takeover performance.

Overall, this dissertation demonstrates the importance of evaluating the cognitive and psychological aspects of emerging technologies and the efficacy of using physiological data as indicators of drivers' cognitive and psychological states.

6.2 Summary of research contributions

This dissertation contributes to two major areas of emerging technologies: real-time travel information and takeover performance under conditional automation.

In the context of real-time travel information, this dissertation provides a comprehensive analysis of several factors (i.e., information characteristics, time stages of interaction with information, and driving environment) that impact the latent cognitive and psychological effects of real-time travel information using drivers' EEG data. It also incorporates these latent information-induced effects along with other measurable factors (i.e., route characteristics, information characteristics, situational factors, and driver attributes) in a hybrid route choice modeling framework to analyze their impacts on drivers' route choices. This study provides valuable insights for several stakeholders. First, information service providers and auto manufacturers should incorporate the cognitive effects of information while designing real-time information and its delivery systems to enhance road safety and user experience. They should also factor the impacts of certain driver attributes, driving environment complexity, and information characteristics (i.e., source and amount) on drivers' cognitive effort and cognitive inattention. Second, the proposed hybrid route choice model incorporates the effects of information characteristics, route characteristics, and situational factors on route choice decisions. This enables traffic operators to better predict drivers' route choices under real-time information provision, which can help them design information dissemination strategies for managing network traffic flows more effectively. It also provides insights on the psychological aspects of real-time information that may impact drivers' route choices. Third, transportation planners can strategize the development of future ATIS infrastructure by incorporating the insights related to the effects of information and route characteristics on driver cognition and route choice behavior. Fourth, the results illustrate that certain driver attributes (i.e., gender) affect route choice decisions indirectly through the latent information-induced cognitive effects. This highlights the opportunities for information service providers and traffic operators to collaborate in designing and disseminating personalized information by factoring driver attributes while achieving their objectives (i.e., enhanced user experience, improved road safety, and better route choice predictions).

This dissertation analyzes the impacts of driver's pre-warning cognitive state using EEG data (for more granular analysis) and the impacts of driver's SA and mental stress using eye-tracking and heart rate measures (for real-world applications) on their takeover performance. There are several contributions of this study in the context of takeover performance under conditional automation. First, a detailed cognitive analysis using EEG provides valuable insights for the design and planning of ADS and takeover warning systems in conditionally automated vehicles. It also enables policymakers to incorporate drivers' cognitive aspects in devising regulatory strategies for using these vehicles. Second, this dissertation identifies a key gap in the literature related to the lack of any comprehensive takeover performance metric that can be used to benchmark the effects of drivers' cognitive state on the overall takeover performance. To address this gap, it proposes a novel, flexible framework to compute a comprehensive takeover performance metric (TOPI) that combines multiple driving performance indicators representing different aspects of takeover performance. By doing so, the study advocates for standardization in measuring takeover performance to provide a consistent and comprehensive measure for different stakeholders (e.g., auto manufacturers, regulatory agencies). Third, the results suggest that the NDRT-induced distraction affects drivers with different driving experience differently. Therefore, a uniform regulation for the use of NDRT in conditionally AVs may reduce their benefits. Policymakers and regulatory agencies can incorporate the interactions between driver attributes and cognitive aspects of using NDRT while devising policies that regulate the use of conditionally automated vehicles. These insights also assist them to develop focused operator training programs and driver licensing strategies by identifying vulnerable population subgroups, and ensure that the transitionary period towards higher levels of automation is smoother and safer. Fourth, the study results show a significant negative effect of novelty in takeover experience on takeover performance, even though drivers practiced taking over in a simplified environment. This has key implications for policymakers to develop operator training programs and driver licensing strategies for conditionally AVs as traditional methods may fall short when preparing the public for operating these vehicles. Fifth, the results also show a significant negative effect of the type of takeover warning (the issuance of TOR) on takeover performance, which indicates that drivers who followed the system recommendation were worse off. This has key implications for auto manufacturers and ADS designers to design takeover warning systems that enhance road safety and promote trust/adaptability. Sixth, the use of eye-tracking and heart rate measures that can be obtained from in-vehicle driver monitoring systems to estimate driver state (SA and mental stress) and their impacts on takeover performance, provides valuable insights for auto manufacturers to design integrated in-vehicle driver monitoring and warning systems. For example, the integrated system can determine the optimal level of the driver's SA using eye-tracking measures and accordingly adjust the ADS and takeover warning system parameters to enhance the user experience by reducing false alarms in conditionally AVs.

6.3 Future research directions

In addition to the future research directions discussed in chapters 2 to 5, the dissertation research can be extended in the following ways. First, the cognitive and psychological effects of real-time information on drivers are not isolated and interact with the cognitive impacts of other factors such as traffic density and trip purpose. Future studies can investigate the interactions of such factors (that are not varied in this study) with information-induced cognitive and psychological effects, and analyze their combined impacts on route choice decisions. Second, future research should analyze the impacts of drivers' pre-information cognitive states (e.g., driver fatigue) on real-time information perception/processing and route choice decision-making behavior. This can enable the development of an integrated real-time information system and driver monitoring system to optimally design the information to be provided based on the driver's psychophysiological states. Third, the proposed takeover performance metric TOPI can be validated, and subsequently calibrated, using expert rater assessment. Given the flexibility of the framework to compute TOPI, it can also be tested in different takeover situations. Fourth, it is important to investigate the effects of the modality of takeover warning (e.g., a combination of visual and auditory warnings) as they may elicit different takeover responses from drivers based on their pre-warning cognitive state in conditionally AVs. Fifth, future research should also examine the effects of different NDRTs on driver's pre-warning cognitive state, SA, and takeover performance. This may provide valuable insights for policymakers to design NDRT-related regulations in conditionally AVs. Sixth, future studies can augment other physiological data (e.g., facial expressions) that can be collected from in-vehicle driver monitoring systems with eye-tracking and heart rate measures for evaluating takeover performance. Seventh, and synergistic with previous research directions, integrated in-vehicle driver monitoring and takeover warning systems for conditionally automated vehicles can be developed that estimate driver state in real-time and predict their response in a takeover situation to provide timely and appropriate warnings to prepare them for the approaching road safety hazards.

APPENDIX A. REAL-TIME TRAVEL INFORMATION SCENARIOS

The table below illustrates the real-time travel information provided to drivers under four information and two traffic congestion scenarios from the two information sources on the freeway and arterial routes.

Source	Scenario	Accident	Current Route	
			Freeway	Arterial
Personal device	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
VMS	NI	Yes/No	Drive carefully Have a nice day	-
	CT	No	I-69: 15 minutes	-
		Yes	I-69: 21 minutes	-
	AT	No	I-69: 15 minutes Allisonville road: 11 minutes	-
		Yes	I-69: 21 minutes Allisonville road: 15 minutes	-
	PI	Yes/No	-	-

The table below shows the information scenario interactions for VMS and personal device on the freeway and arterial routes. Information on the arterial route was provided via personal device only. 13 of the possible 32 (4 information scenarios × 2 information sources × 2 routes × 2 traffic congestion) scenario combinations at the first information provision location were used in the study experiments.

		Personal device			
		NI	**CT**	**AT**	**PI**
VMS (Freeway)	**NI**	✓	✓	✓	✓
	CT	✓	✓	×	×
	AT	✓	×	✓	✓
	PI	×	×	×	×
No VMS (Arterial)	**-**	✓	✓	✓	✓

APPENDIX B. UNUSED VARIABLES AND ESTIMATED VARIANCES FOR HYBRID ROUTE CHOICE MODEL

TESTED EXPLANATORY VARIABLES

The following table summarizes the list of explanatory variables that were tested but were not included in the final hybrid route choice model as they were found to be statistically non-significant ($p > 0.1$).

Category	Explanatory Variables
Route characteristics	None
Driver attributes	Age, education, income, driving experience (based on driver's license)
Situational factors	None
Real-time information characteristics	Indicator variables for information from multiple sources, prescriptive information, and VMS

MODEL (CO)VARIANCES

The table below presents variances and covariances of the estimated hybrid route choice model.

Variable	Estimate	Std. Error
$\mathcal{I}_F^\beta$	0.003***	0.000
$\mathcal{I}_T^\beta$	0.002***	0.000
$\mathcal{I}_P^\beta$	0.001***	0.000
$\mathcal{I}_O^\beta$	0.002***	0.000
$\mathcal{C}_F^\alpha$	0.015***	0.001
$\mathcal{C}_T^\alpha$	0.014***	0.001
$\mathcal{C}_P^\alpha$	0.007***	0.001
$\mathcal{C}_O^\alpha$	0.013***	0.001
U	0.922***	-
$\mathcal{I}^\beta$	0.003***	0.000
$\mathcal{C}^\alpha$	0.007***	0.001
$\mathrm{cov}(\mathcal{I}^\beta, \mathcal{C}^\alpha)$	0.001***	0.000

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

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