

Hybrid Route Choice Model Incorporating Latent Cognitive Effects of Real-Time Travel Information Using Physiological Data

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Abstract

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

Keywords: Route choice, Real-time information, Driver cognition, Driver physiology, Electroencephalography (EEG), Driving simulator

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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; 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 (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). Latent class route choice models that explicitly consider latent heterogeneity among drivers based on several factors such as personality traits and experience have also been proposed in the past (Alizadeh et al., 2019; Tawfik & Rakha, 2013). Although most existing models either use stated preference or revealed preference approaches, a few studies have proposed route choice models under real-time travel information provision that leverage both types of approaches simultaneously, either through data collection mechanism (Bogers et al., 2005) or through the

model structure (Shiftan et al., 2011), to mitigate their limitations. 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 hybrid 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. Although using EEG in real-world applications is less practical compared to other physiological data (e.g., eye-tracking data), it enables estimating a more detailed profile of drivers' cognitive state by directly analyzing brain electrical activity patterns (e.g., EEG signal band powers) in different regions of the brain (Abhang et al., 2016; Agrawal et al., 2020). Raw EEG signals are contaminated by low- and high-frequency noise from various sources (e.g., eye or head movements) that, if untreated, can lead to misanalysis. However, previous studies have illustrated that decontaminated EEG data can provide useful insights on human cognition in a wide range of driving and non-driving tasks (Berka et al., 2004, 2005). 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 (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. However, previous studies have not used EEG-based measures to incorporate latent cognitive effects of real-time information in route choice behavior models. 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 the latent cognitive effects of drivers' interactions with real-time information on their route choice behavior 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 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 2 presents the conceptual hybrid route choice modeling framework. Section 3 outlines the driving simulator experiment design, data collection procedures, and data preprocessing methods. Section 4 discusses the model estimation results. Section 5 summarizes the study findings, and concludes the paper by providing some future research directions.

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 1 presents a conceptual framework of the proposed hybrid route choice model.

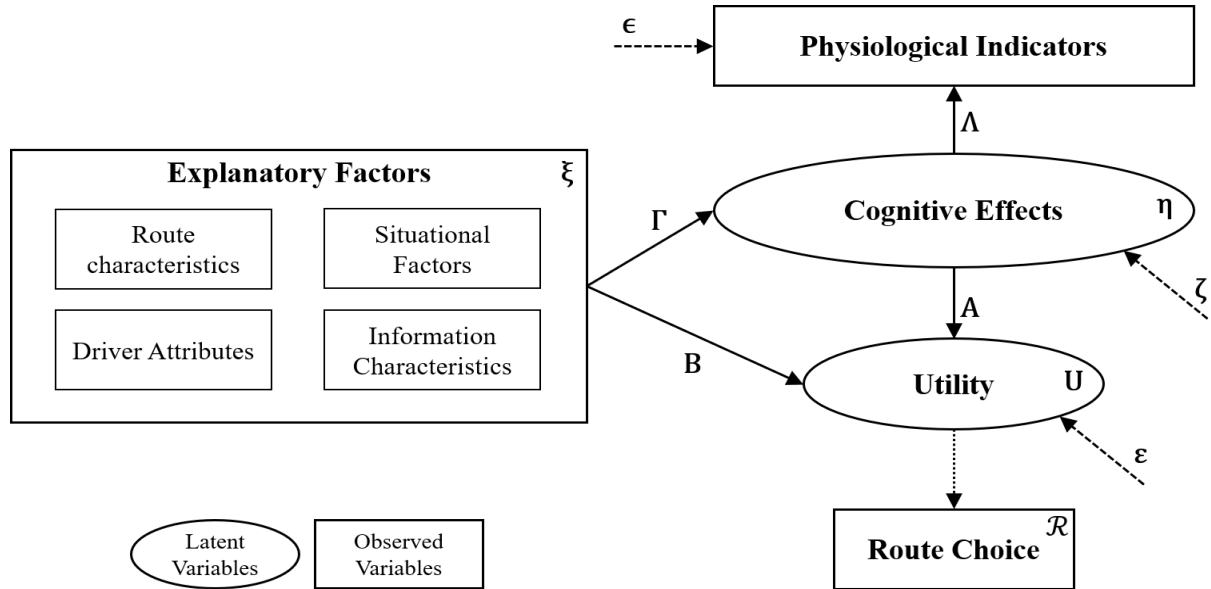


Figure 1 Conceptual hybrid route choice model with physiological indicators

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. (1).

$$\mathbf{y} = \mathbf{\Lambda}\boldsymbol{\eta} + \boldsymbol{\epsilon}; \quad \boldsymbol{\epsilon} \sim N(0, \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}}) \quad (1)$$

In Eq. (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. (2), and for the random utilities is given by Eq. (3).

$$\boldsymbol{\eta} = \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta}; \quad \boldsymbol{\zeta} \sim N(0, \boldsymbol{\Sigma}_{\boldsymbol{\zeta}}) \quad (2)$$

$$\mathbf{U} = \mathbf{A}\boldsymbol{\eta} + \mathbf{B}\boldsymbol{\xi} + \boldsymbol{\epsilon}; \quad \boldsymbol{\epsilon} \sim N(0, \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}}) \quad (3)$$

$$\Pr(\mathcal{R} = 1|\mathbf{U}) = \Phi(\mathbf{U}) \quad (4)$$

In Eq. (2), $\boldsymbol{\xi}$ is a vector of explanatory variables, $\boldsymbol{\Gamma}$ 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), $\mathbf{U}$ 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 ($\boldsymbol{\epsilon}$) are assumed to be identical and independently normally distributed with mean of zero. Eq. (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. Methodology

3.1. Apparatus

3.1.1. Driving simulator

A medium-fidelity fixed-base driving simulator (AVSimulation, 2020) was used to collect data for this research (see Figure 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 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). Drivers (study participants) could choose between two routes (freeway and arterial) to reach their destination, as illustrated in Figure 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 simulated views of the two routes were designed with appropriate built environment, with more scenery and few or no buildings on the freeway route, and sidewalks, well-spaced trees, and more buildings on the arterial route (Figure 4). 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. More details on the route characteristics are presented in Table 1. 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 Figure 3, 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 3.2 for details).

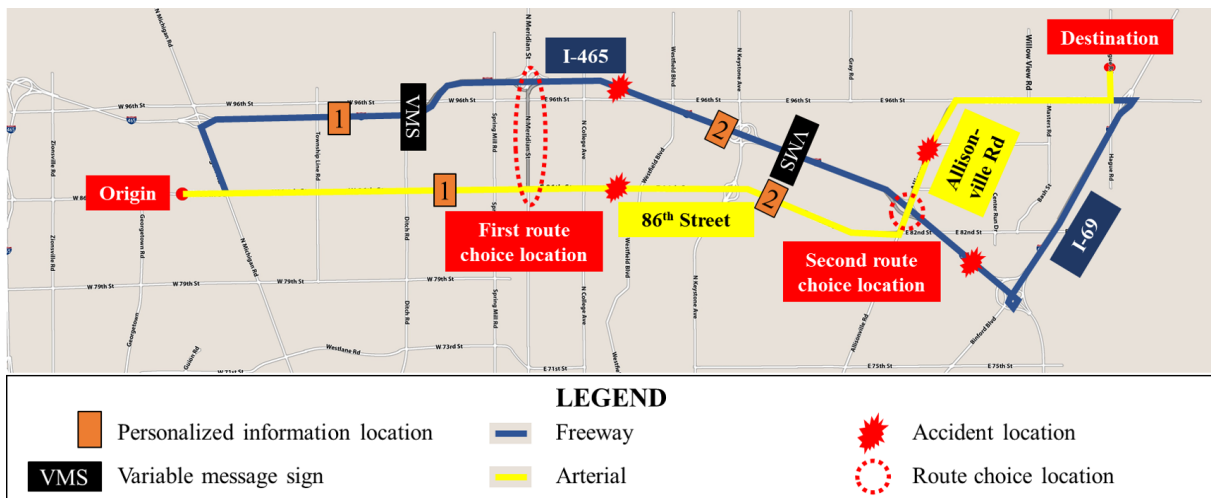


Figure 3 Experiment setup



(a) Freeway route: more scenery with few or no buildings



(b) Arterial route: sidewalk, well-spaced trees, and roadside buildings

Figure 4 Simulated view of the two routes with rear-view and side-view mirrors

Table 1 Route characteristics

Characteristic	Freeway route	Arterial route
Distance to destination	16 miles	11 miles
Travel time to destination (under normal traffic conditions)	21 minutes	25 minutes
Speed limit	65 mph	50 mph
Number of signalized intersections (from origin to destination)	3	17
Variable message signs	2	0

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 5. Each EEG channel corresponds to a specific brain region or lobe as illustrated in Table 2.

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).

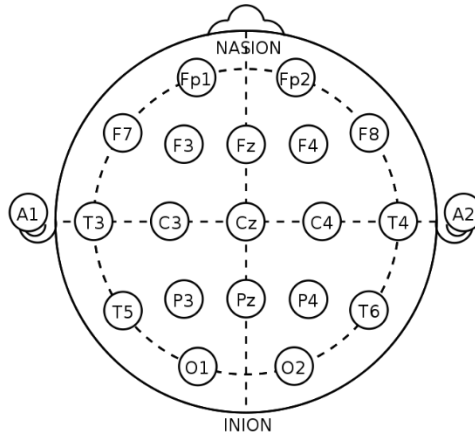


Figure 5 EEG electrode placement (source: Wikipedia, 2019)

Table 2 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

3.1.3. 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 2.

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), 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. 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 I and Appendix II. To reduce the possible combinations of scenarios, eight scenario sets were designed with each set containing three runs. The use of these eight scenarios among participants was balanced. More details on the scenario sets can be found in Appendix III. 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 I).

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. A verbal confirmation was obtained from participants on their level of comfort in operating the simulator. Those who did not feel sufficiently comfortable at this stage were provided with an option to continue practicing driving in the simulator until they felt so. 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 the assigned scenario set. The order of scenarios within a scenario set was randomized. 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. Participants spent about 2.5 to 3 hours in the laboratory, with approximately 1 to 1.5 hours of driving in three experiment runs.

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 2). 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 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 $\mathcal{J}_r^b$ 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).

3.5. 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 6 shows the age and gender distribution of these participants. Participants were compensated (with a maximum of \$60) based on the point-based reward system discussed in section 3.3.

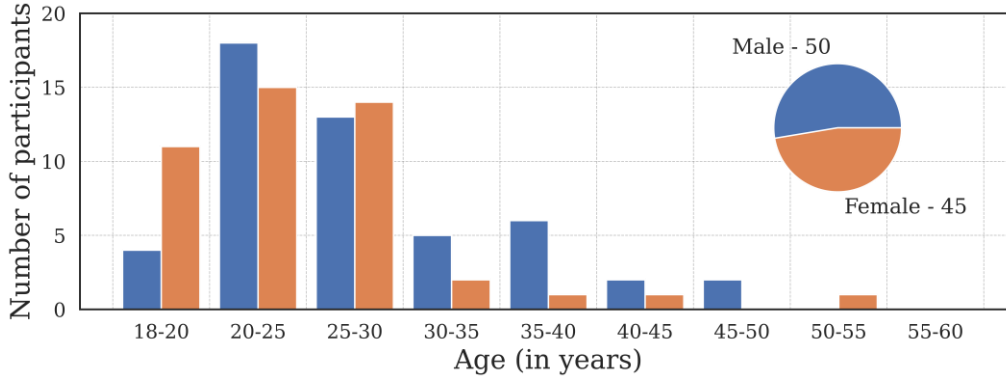


Figure 6 Age and gender distribution of the participants

4. Results and discussion

4.1. Descriptive analysis

This study collected data from 285 experiment runs. Figure 7 illustrates the information scenario distribution grouped by the traveled route for all experiment runs.

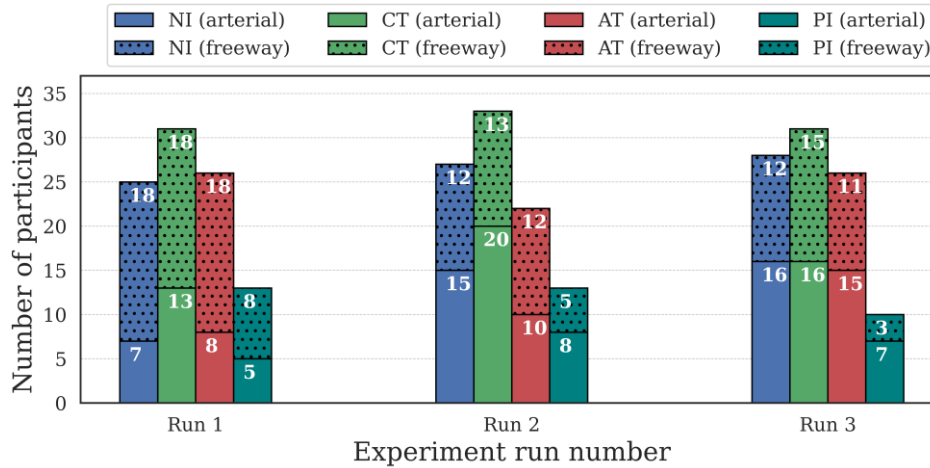


Figure 7 Information scenario distribution by route and experiment run

The observed route choices for each scenario on each route are presented in Table 3. It can be seen that the overall observed behavior on the two routes is similar under no information provision, but is noticeably different when real-time information was provided. This indicates the importance of the current route in the route switching decision under information provision.

Table 3 Observed route switching behavior by route and information scenario

Information Scenario	Arterial		Freeway	
	Did not switch route ($\mathcal{R} = 0$)	Switched route ($\mathcal{R} = 1$)	Did not switch route ($\mathcal{R} = 0$)	Switched route ($\mathcal{R} = 1$)
NI	31	7	34	8
CT	6	43	31	15
AT	2	31	20	21
PI	3	17	8	8

4.2. EEG and latent cognitive effects

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., 2016), 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 2) 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 0.6.6 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 ($\mathcal{J}^\beta$) 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 (Lin et al., 2018), and focused external attention (Abhang et al., 2016). 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.

4.3. Model estimation results

Next, we estimated the hybrid route choice model, as illustrated in Figure 8, with the latent variables and explanatory variables using weighted least square mean and variance adjusted (WLSMV) estimator implemented in the lavaan package. Explanatory variables with non-statistically significant main or interaction effects ($p > 0.1$) were not included in the final model (see Appendix IV 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 4.

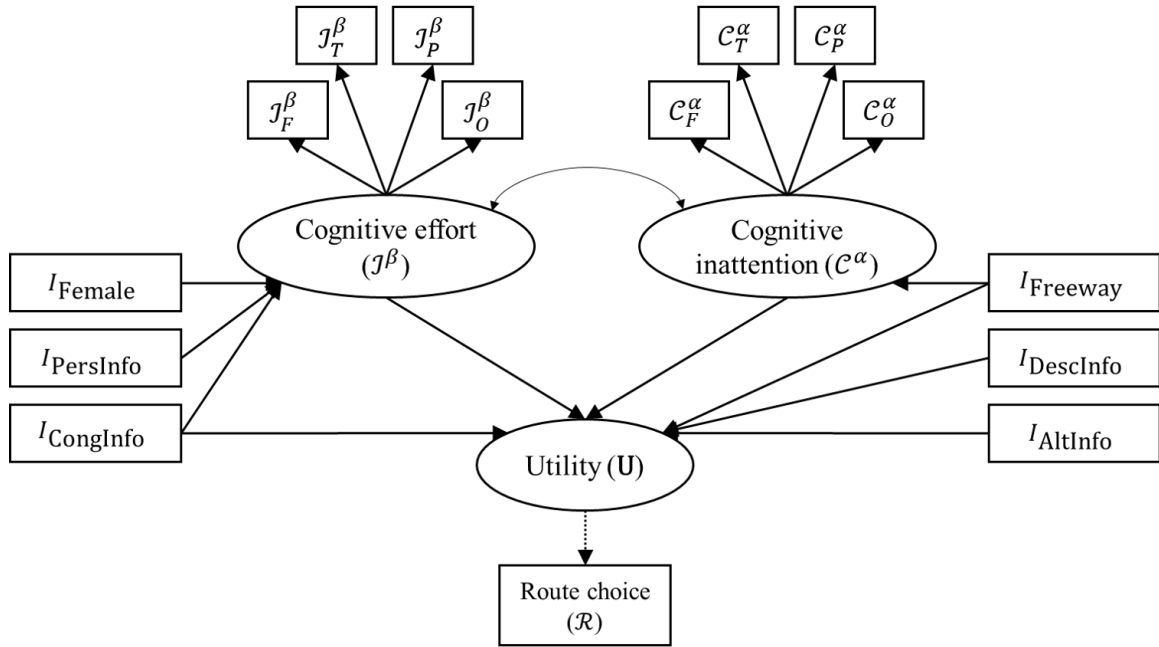


Figure 8 Estimated hybrid route choice model structure

Table 4 Variable description

Variable	Description
$\mathcal{R}$	Indicator for route change (1: switch from the current route; 0: otherwise)
U	Random utility (probit)
j^β	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)

Variable	Description
$I_{DescInfo}$	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. However, it should be noted that χ^2 depends on the sample size and is a reasonable model fit measure for models with sample size between 75 and 200 (Kenny, 1979). In addition, the estimated model is compared to a more restrictive nested model with the coefficients of the latent variables (i.e., $\mathcal{J}^\beta$ and $\mathcal{C}^\alpha$) set to 0. The model fit measures for the estimated hybrid model, estimated nested model, and the null model, as presented in Table 5, indicate a good model fit for the hybrid model with latent variables.

Table 5 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

The measurement model results, as illustrated in Table 6, 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. Higher EEG band power in the temporal and occipital regions are associated with auditory and visual information processing (Abhang et al., 2016; Friederici, 2011), and in the parietal region with verbal-semantic processes and visual attention (Bisley & Goldberg, 2010; Doppelmayr et al., 2005). This suggests that processing and utilizing real-time travel information and scanning the road environment for visual cues had a considerable impact on the latent cognitive variables. The estimated model covariance (double-headed curved arrow in Figure 8) 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 V.

Table 6 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

Table 7 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 7 Structural model estimation results

Variable	$\mathcal{J}^\beta$		$\mathcal{C}^\alpha$		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: $\Pr(\mathcal{R} = 1 \mathbf{U})$					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 7. 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 $\mathcal{C}^\alpha$) 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 adequate 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 ($\mathcal{I}^\beta$) 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 $\mathcal{I}^\beta$, $\mathcal{C}^\alpha$ 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. It should be noted that travel time, travel cost, and other level of service attributes are not explicitly considered in the route choice model as they are captured by indicators for the freeway route and traffic congestion information. 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).

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. Although gathering EEG data is currently impractical in the operational context, it provides comprehensive insights on the latent cognitive effects that can assist the design and planning of real-time information and its dissemination strategies. 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. Several elements of experiment design such as general information characteristics, network-level setup, responsive ambient traffic, and realistic route choice situation under real-time information provision (where participants' route choices may affect time spent driving and their compensation) make the proposed model transferable to the real-world, but it may require calibration depending on the scenario.

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.

The limitations of this study and 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, the possible effects of driving fatigue during the experiment, which could affect participants' behavior, are not analyzed in this study. Fourth, 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. Further, future research can expand the proposed model to situations with more than two alternative routes for enhancing its transferability.

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Appendix I

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	Information Scenario	Congestion Scenario	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
	PI	Yes/No	-	-
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	No	-	-
		Yes	-	-

Appendix II

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 III

The table below illustrates the information scenarios and traffic congestion scenarios at the first information provision location for the eight scenario sets used in this study. The order of runs within a scenario set was randomized. Note that public travel information was available only on the freeway route, which affects the information scenario based on the participant's pre-trip route choice (i.e., before the first information provision location).

Set Number	Road Accident	Personalized Travel Information	Public Travel Information	Information Scenario
1	No	AT	AT	AT
	Yes	AT	AT	AT
	Yes	PI	NI	PI
2	No	NI	NI	NI
	No	CT	CT	CT
	Yes	CT	CT	CT
3	Yes	CT	NI	CT
	Yes	CT	CT	CT
	Yes	AT	AT	AT
4	No	CT	CT	CT
	No	AT	NI	AT
	No	AT	AT	AT
5	No	NI	AT	NI (arterial) / AT (freeway)
	No	AT	NI	AT
	Yes	AT	NI	AT
6	No	NI	CT	NI (arterial) / CT (freeway)
	No	CT	NI	CT
	No	CT	NI	CT
7	Yes	NI	AT	NI (arterial) / AT (freeway)
	Yes	PI	NI	PI
	Yes	PI	AT	PI

8	No	NI	NI	NI
	No	NI	CT	NI (arterial) / CT (freeway)
	No	CT	CT	CT

Appendix IV

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

Appendix V

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

Variable	Estimate	Std. Error
J_F^β	0.003***	0.000
J_T^β	0.002***	0.000
J_P^β	0.001***	0.000
J_O^β	0.002***	0.000
C_F^α	0.015***	0.001
C_T^α	0.014***	0.001
C_P^α	0.007***	0.001
C_O^α	0.013***	0.001
U	0.922***	-
J^β	0.003***	0.000
C^α	0.007***	0.001
$\text{cov}(J^\beta, C^\alpha)$	0.001***	0.000

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