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Modeling Drivers in Route Diversion Behavior During Congestion: A Pilot Study

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EXCUTIVE SUMMARY

This study investigates factors influencing drivers' decisions to divert their routes in response to congestion and delays on coastal road networks. Key variables examined include information-seeking behavior, travel time, trip factors, demographics, and disruption scenarios such as emergency evacuations. The research utilized a comprehensive survey distributed to U.S. drivers to assess diversionary choices on coastal road networks based on travel habits, information sources, and demographic characteristics. The survey included questions about routine travel behaviors, sources of traffic information, and intended diversion actions under various scenarios, including severe weather events common to coastal regions. Logistic regression models, including multinomial and ordinal logit models, were employed to analyze the data. Results indicate that receiving real-time traffic information significantly increases the likelihood of diversion, particularly during work zones and adverse weather conditions such as fog or heavy rain. Travel time and delays emerged as critical motivators for route changes in coastal areas, with drivers experiencing longer delays being more likely to divert. Demographics impact diversion behavior: drivers aged 18 to 30 tend to choose "No Divert" during morning commutes and are less often "Unsure" during afternoon commutes. In contrast, drivers with incomes below $100,000 are more likely to be "Unsure" in the morning and less likely to choose "No Divert" in the afternoon. These findings contribute to a deeper understanding of driver behavior on coastal road networks, highlighting the importance of timely and reliable traffic information, especially during natural disasters. The study underscores the need for traffic management strategies and driver information systems that cater to different demographic groups and preferences in a variety of coastal areas. By tailoring these strategies, transportation agencies can better manage traffic flow and reduce congestion, ultimately enhancing the overall efficiency and safety of the transportation network in regions vulnerable to coastal hazards.

Keywords: Route diversion, stated preference survey, traffic disruption, emergency evacuation, logistic regression models, attitudes and behavior

1- INTRODUCTION

Traffic delays due to roadway disruptions is a persistent problem for coastal road networks in countries around the world. The cost of traffic delays exceeds $100 billion annually in the U.S. in terms of wasted working hours and fuel. When faced with unexpected congestion, drivers frequently divert to an alternative route to reach their destination while avoiding as much further delay as possible. Areas near coastlines face unique vulnerabilities to hazards such as hurricanes and tsunamis, possibly causing widespread damage to transportation networks. While driver route choice is relatively well understood in normally operating, undisrupted networks, the re-routing decisions of drivers in disrupted networks are more complex and not as well understood. The interaction of many factors and preferences makes this diversion behavior difficult to describe, model, and predict; however, a well-designed travel survey is uniquely positioned to collect data on many of these topics as they relate to diversion behavior in a variety of driving scenarios.

The current study aims to improve the understanding of which factors are most influential in the diversion decisions of coastal drivers by means of a stated preference travel survey, especially during morning and afternoon commute trips. Data was collected on a wider variety of factors than previously investigated, including traffic information/routing guidance acquisition preferences, data pertaining to the likelihood of diversion during different trip purposes, disruption types, and a variety of trip and network characteristics, as well as other personal and demographic characteristics. By using logistic regression models to analyze and predict diversion choice behavior, significant relationships were found between likelihood of diversion and several demographic, information-, disruption-, and time-, and trip-related variables such as age, income, information source and timing, average delay times, and road type among others.

The findings of this study can be useful for preparing commonly used alternate routes for additional traffic volumes during inclement weather or rush hour traffic jams. The findings on information acquisition and compliance attitudes can help improve the quality of travel advisories delivered to drivers in real-time to induce certain driving behaviors. Additionally, as the market penetration rate of autonomous and connected vehicles continues to rise, it is important to improve our understanding of human routing decisions in order to accurately model and predict traffic flows in a wide variety of scenarios for both short- and long-term transportation investment decisions.

The next section reviews relevant research from the body of literature, introduces potential influencing factors, and presents hypotheses created for this study. The subsequent section first describes the data collected from a driver behavioral survey conducted in the U.S. The paper then summarizes the findings of the logit regression analyses and concludes with a discussion of the implications of those findings.

2- LITERATURE REVIEW

The authors conducted a thorough literature review and tested a wide range of influential factors, but this section only presents those hypotheses of greater interest for discussions.

2-1- En-Route Traffic Information Seeking Behavior

Traffic information significantly impacts drivers' en-route routing choices, and the delivery methods for this data have evolved over the decades. While Khattak et al. (1993b) found that prior experiences influenced diversion decisions more than real-time information, more recent studies highlight the significant impact of traveler information on driver decision-making during congestion. Schroeder and Demetsky (2011) used loop detector data to assess the impact of Varible-Message Sign (VMS) information on driver diversion behavior, finding that detailed VMS information, such as alternate route directions, increased driver diversion. Gan and Ye (2013) also found that VMS information influenced more experienced drivers to divert, while middle-aged drivers were less likely.

Drivers increasingly rely on in-vehicle GPS navigation systems and smartphone apps like Waze and Google Maps. Yamsaengsung and Papasratorn (2018) found that drivers perceive high-quality information from these apps but do not always trust the recommended routes. Similarly, Khoo and Asitha (2016) found that drivers who viewed smartphone app information as reliable and accurate were more willing to divert. However, there may be differences in real-time information-seeking behavior among drivers. Younger drivers are expected to seek real-time information more frequently than older drivers, who tend to use driver assistance technology less and face more challenges with it (Cirella et al., 2019; Gandolfi, 2020; Payyanadan et al., 2018; Pohlmann and Traenkle, 1994; Dotzauer et al., 2014). Spyropoulou and Antoniou (2015) showed that young drivers are more likely to divert when receiving occasional online information, while older drivers are more likely to divert with regular radio information. The following hypothesis was created based on past studies and tested in the current study.

H1: Drivers who report receiving information on traffic conditions and routing guidance are more likely to divert than those who do not seek such information.

2-2- Route Diversion Behavior in Different Disruption Scenarios

Most previous studies on route diversion behavior have focused on single disruption scenarios such as work zones (Huchinson et al., 1984; Horowitz et al., 2023; Memarian et al., 2019), planned special events (Lei-Lei et al., 2012; Kwoczek et al., 2014), rush hour congestion (Khattak et al., 1993a; Spyropoulou and Antoniou, 2015), adverse weather events (Khattak and Palma, 1997; Elhenawy et al., 2021), and incidents (Kwon et al., 2006; Knoop et al., 2008; Knoop et al., 2009; Pan et al., 2015). Some studies have examined diversion willingness across multiple disruption types. For example, Spyropoulou & Antoniou analyzed VMS information impact on driver diversion behavior for incidents, planned special events, and work zones. However, no studies have investigated how drivers react to the five different disruption scenarios explored in this study. This research aims to determine whether individuals are more likely to divert in one type of disruption compared to others when controlling for other influencing factors. These discussions lead to the following hypothesis:

H2: Drivers who are unlikely to divert during adverse weather events and work zones are less likely to divert during commute trips.

2-3- Effects of Time-Related Factors on Driver Behavior

Several studies in travel diversion research have found that travel time is the most influential factor in drivers choosing to divert from a route. In a behavioral study using discrete choice models of diversion and return behavior, Khattak et al. (1993b) demonstrated that longer delays and travel times increased the probability of diversion. Similarly, Al-Deek et al. (2012) used a multinomial logit model to estimate and quantify the odds of selecting a diversion alternative over remaining on a current route. Their results indicated that longer travel times and delays were the most prominent factors associated with greater route diversion.

In a later study, Khattak and Khattak (1998) analyzed drivers' spatial knowledge and en route response to unexpected delay information in Chicago and the San Francisco Bay Area. They found that the natural tendency to divert from a route increases when there is a higher-than-usual travel time alongside shorter alternate route travel times nearby. Drivers who are naturally more cautious in their decisions are more likely to divert to avoid unexpected delays in travel time. Gan and Ye (2012) conducted a behavioral study focusing on urban freeway users in China. Their analysis revealed that travel time savings served as a positive factor in driver diversion. Despite the studies being conducted in vastly different geographical locations, reduced travel time remained the most influential factor in route diversion.

Gudishala et al. (2020) analyzed the differences in the level of congestion between a freeway in Baton Rouge, Louisiana, and the surrounding local roads that trigger traffic to divert from the freeway. Given the prior emphasis on travel time importance in route diversion, their study aimed to measure the time lag between the onset of congestion and diversionary behavior and relate it to a Travel Time Index (defined as the ratio of peak travel time to free-flow travel time). The results indicated that diversionary behaviors often occur when the Travel Time Index is 1.5 or above on nearby arterials. The stability of traveler diversion tactics was observed in terms of variance in time lag between traffic incidents, showing high values (50 and 54), indicating that diversionary behavior is not consistent from incident to incident. The following hypothesis was created based on past studies and tested in the current study.

H3: Drivers who regularly face longer traffic delays during typical commute trips are more likely to divert during those commute trips.

2-4- Effects of Trip Factors on Driver Behavior

Several studies highlight the importance of perceived congestion levels in route diversion. Xu et al. (2011) used a probit model in Shanghai to analyze key factors in driver diversionary behavior, finding that drivers rely on visible downstream congestion to decide on route changes. This model's accuracy was confirmed by a stated preference survey. Khoo and Asitha (2016) found that drivers are more responsive to changes in traffic density than speed when perceiving congestion. Their study suggested that drivers' travel decisions dynamically change with perceived congestion levels, typically categorized as low, medium, or high. At medium congestion levels, drivers tend to delay departure, while at high levels, they are more likely to cancel trips.

Driver familiarity with an area also influences diversionary behavior. Richards et al. (1978) observed that drivers familiar with a route and its alternate options are more likely to divert to save time, even without guidance. Khattak et al. (1994) found that about 40% of San Francisco Bay Area commuters change routes to avoid delays. In a follow-up study, Khattak and Khattak (1998) linked longer residency in an area to increased likelihood of discovering and using alternate routes to avoid congestion, thus improving travel efficiency. These discussions lead to the following hypothesis:

H4: Drivers who express uncertainty about the effects of trip-related factors are also more unsure about their likelihood of diversion during morning and afternoon commutes.

2-5- Demographics

The sections that follow highlight and briefly summarize prior work to identify how individuals differ in making decisions when analyzing specific demographics, particularly age and income.

Prior studies also considered the following as potential influential factors, such as area type (Pucher & Renne, 2005; Adeyemi & Paul, 2021; Zhou et al., 2022; Chen & Deng, 2022; Ying et al., 2020; Farrell et al., 2015).

Age

Prior studies have examined the impact of age on technological adoption and decision-making behaviors. Phillips and Sternthal (1977) found that aging leads to reduced social involvement, increased narcissism, less conformity, decreased suggestibility, and declining persuasion. John and Cole (1986) showed that problem-solving abilities are not necessarily better in younger individuals. Yoon (1997) found that older individuals prefer simpler information and that decision-making is more detailed during peak times for all ages. Age also affects technology adoption. Czaja et al. (2006) reported that older individuals are less likely to adopt new workplace technologies due to computer anxiety. Morris and Venkatesh (2004) noted that older consumers are more influenced by social norms against new technology. In transportation, Abraham et al. (2017) found that older drivers are less willing to use fully autonomous vehicles, while younger drivers are more open to them.

Income

Income levels significantly influence driver behavior in various aspects. Higher-income individuals often have greater access to newer, safer, and more reliable vehicles, which can lead to safer driving practices and lower crash rates. For instance, a study by Elvik (2010) found that higher-income drivers are less likely to be involved in traffic accidents due to their ability to afford advanced safety features in their vehicles. Conversely, lower-income drivers may experience more stress and fatigue due to longer commutes or multiple jobs, which can negatively impact their driving performance. Research by Stucki et al. (2017) indicates that lower-income drivers are more likely to engage in risky behaviors, such as speeding and distracted driving, often as a result of economic pressures and time constraints. Additionally, income disparities can affect the likelihood of maintaining proper vehicle upkeep, with lower-income individuals potentially neglecting essential maintenance due to financial limitations, leading to increased safety risks (2005). These income-related differences underscore the complex relationship between economic status and driving behavior, highlighting the need for policies that address these disparities to improve road safety for all socioeconomic groups. These discussions lead to the following hypothesis:

H5: Older drivers and drivers who earn a lower annual household income are less likely to divert during commute trips in comparison to younger drivers and higher earners.

3- METHODOLOGY

This section describes the survey instrument and the data collected, as well as a description of the analysis approach used in this study. The findings of this process provided the results on which to determine whether each hypothesis presented was to be rejected or not.

3-1- Survey and Data Description

The survey questionnaire was developed through a series of small-scale pilot studies used to gauge overall comprehension, question clarity, average completion time, and the need for any additional questions. The final survey instrument was composed of 58 questions in four sections to investigate potential factors that may influence coastal drivers' en-route diversion choice behavior. This survey was given approval from the Institutional Review Board at Louisiana State University.

The first section in the survey focuses on understanding routine travel (e.g., continuous data on commute durations, delays, and tolerances). The second section is to understand what sources an individual may seek for traffic information and when that happens. The third section is to collect individuals' intended route diversion behavior in various scenarios. Many of the questions were structured as 5-point Likert scale responses, in which a numeric rating between 1 (indicates "strongly disagreed") and 5 (indicates "strongly agreed") could be selected to indicate how strongly the respondent agreed or disagreed with a given statement. The Likert scale is commonly used in statistics, marketing, and the social sciences to quantify and relate perceived and experienced "feelings" of survey respondents. The scale is also useful for identifying statistical variation among subgroups in the survey samples. The last section in the survey collects socio-demographic information of an individual (age).

The survey was created via an online platform called Qualtrics™ and was distributed via Prolific™, which connects researchers with potential survey participants and provides a small incentive to those who complete the survey. An individual needed to be an adult with a U.S. driver license to be eligible for survey responses. A total of 1,051 survey responses were collected in 4.5 hours (from 11:30am to 4:00pm) on December 16, 2022. The median completion time was about six minutes; survey participants were paid $1.40 for their time ($13.70/hour). Of the 1,051 collected responses, 810 responses were found to be complete and eligible for further analysis. Table 1 presents statistics for some of the survey questions discussed within this study.

3-2- Statistical Analysis Approach

Due to the nature of the data collected from the survey, logistic regression was selected as the main form of analysis for this study. Multinomial logit (MNL) models and ordinal logit (OL) models were selected for this dataset for multiple reasons. This data was originally intended to represent an ordinal set of responses from low likelihood of diversion to high, including a neutral option ("Unsure/it depends") for those who neither agree nor disagree. However, it was unclear whether this ordinal nature would in fact be observed or if the variables would exhibit more categorical characteristics. Therefore, both multinomial and ordinal logit models were developed to explore the nature of these relationships. Preliminary testing showed that the sample sizes were insufficient to support conclusive findings when considering all 5 response levels separately. Interestingly, many of the initial tests showed consistent relationships between respondents who selected Unsure for multiple variables, so the 5-point scale was simplified to a 3-point scale: disagree (No Divert), neutral (Unsure), and agree (Divert). With this configuration the results may also be able to account for the effects of uncertainty on driver diversion decision-making.

SPSS and NLOGIT were employed to develop the logistic regression models utilized in this study. In developing multinomial logit models for both dependent variables, an exhaustive analysis of the available independent variables was carried out, and all significant variables were retained in the model. Next a Pearson correlation test was conducted on this selection of independent variables to identify and remove any potential effects of multicollinearity, and a list of 33 and 29 predictor variables were included in the final MNL models for diversion during morning and afternoon commutes, respectively. The creation of the ordinal logit models followed a similar process to the multinomial models previously described. Initial tests of each independent variable for both morning and afternoon models provided a list of significant predictor variables

Table 1. Data Descriptions

Variable	Description	Range	Mean	Std. Dev.
Disruption Type				
Work Zone	I would divert from my normal route when encountering a work zone (i.e., construction, maintenance, work crew) (in Likert scale)	[1, 5]	3.50	1.08
Weather	I would divert from my normal route when encountering adverse weather (i.e., slow-downs due to rain, fog, snow) (in Likert scale)	[1, 5]	3.13	1.27
PSE	I would divert from my normal route when encountering a planned special event (i.e., concert, sports game, holiday traffic) (in Likert scale)	[1, 5]	4.13	0.95
PSE Aware	I am aware of planned special events that might affect traffic along my commute (in Likert scale)	[1, 5]	3.47	1.03
Incident	I would divert from my normal route when encountering an incident (i.e., crash, stalled vehicle, object on road) (in Likert scale)	[1, 5]	4.12	0.92
Information Seeking Behavior				
Information	I often seek out traffic information/routing guidance (in Likert scale)	[1, 5]	3.34	1.30
My Way	When receiving traffic information, I often disregard routing guidance and choose my own route instead (in Likert scale)	[1, 5]	2.42	1.07
Cancel	I often cancel trips or change destinations due to traffic information about congestion (in Likert scale)	[1, 5]	2.07	1.05
When Congestion	Whether a driver seeks traffic/routing information only when encountering congestion or unexpected delays (1 = Yes)	[0, 1]	0.32	0.47
When Before	Whether a driver seeks traffic/routing information only before departure (1 = Yes)	[0, 1]	0.16	0.37
When Multiple	Whether a driver seeks traffic/routing information multiple times throughout a trip (1 = Yes)	[0, 1]	0.28	0.45
Source Radio	I receive information about traffic conditions or routing guidance from radio advisories (1 = Yes)	[0, 1]	0.18	0.39
Source TV	I receive information about traffic conditions or routing guidance from television advisories (1 = Yes)	[0, 1]	0.05	0.21
Source Web	I receive information about traffic conditions or routing guidance from website advisories (1 = Yes)	[0, 1]	0.02	0.16
Source Visual	I receive information about traffic conditions or routing guidance from visual confirmation/direct observation (1 = Yes)	[0, 1]	0.40	0.49
Number of Sources	Total number of sources from which respondents reported receiving information	[0, 7]	1.80	1.10
Time-Related Factors				
Travel Time Save	I divert as soon as I think it will save time (in Likert scale)	[1, 5]	3.68	1.02
Travel Time Reliability	Travel time consistency/reliability is important to me and my route choice decisions.	[1, 5]	4.28	0.72
AM Delay	How much time a driver reports spending in congestion during a typical morning commute trip, from home to work (in minutes)	[0, 90]	7.89	8.41
PM Delay	How much time a driver reports spending in congestion during a typical afternoon commute trip, from work to home (in minutes)	[0, 90]	11.99	10.48

Longer	I will not divert if the diversion route takes longer than staying on the normal route (reverse-coded; in Likert scale)	[1, 5]	1.98	1.07
Sit Time	How long driver reports sitting in congested traffic before deciding to reroute, in minutes	[1, 60]	12.72	7.47
Sit Time <15	Whether a driver reports sitting in congested traffic for less than 15 minutes before deciding to reroute (1 = Yes)	[0, 1]	0.62	0.49
Sit Time <20	Whether a driver reports sitting in congested traffic for less than 20 minutes before deciding to reroute (1 = Yes)	[0, 1]	0.82	0.39
Trip Factors				
Return	After diverting, I am likely to return to the normal route after passing the congested area (in Likert scale)	[1, 5]	3.78	1.06
Smooth	Even if it might take longer, I would choose a smoothly flowing route over a congested route (in Likert scale)	[1, 5]	3.61	1.13
Distance to Destination	I am more willing to reroute if I am far from my destination (in Likert scale)	[1, 5]	3.73	0.99
Passenger	I drive differently when a passenger is present (in Likert scale)	[1, 5]	2.98	1.33
Social	I am more willing to reroute if I see other drivers also diverting (in Likert scale)	[1, 5]	3.94	0.94
Freeway	I would rather reroute onto a freeway than onto a local street (in Likert scale)	[1, 5]	3.12	1.20
Options	I am more willing to reroute if there are multiple rerouting options than if there is only one (in Likert scale)	[1, 5]	3.54	1.07
Prefer Familiar	I prefer driving on routes that are familiar to me (in Likert scale)	[1, 5]	4.54	0.70
Congest	Congestion is a problem for me during my typical commute (in Likert scale)	[1, 5]	3.11	1.34
Road Freeway	Whether a driver typically drives on a freeway as the main route of their commute (1 = Yes)	[0, 1]	0.43	0.49
Sure	When diverting, I feel confident that I am making the best choice (in Likert scale)	[1, 5]	3.46	1.11
Stops	The number of stops/traffic signals on a diversion route has a significant impact on my willingness to choose that route (in Likert scale)	[1, 5]	3.38	1.06
Demographics				
Age 18-30	Whether a driver is between the ages of 18 and 30 (1 = Yes)	[0, 1]	0.29	0.45
Low Income	Whether a driver has an annual household income of less than $100,000 per year (1 = Yes)	[0, 1]	0.71	0.45
Job Public	Whether a driver has a public sector job (1 = Yes)	[0, 1]	0.26	0.44
Adventurous	I consider myself an adventurous driver (in Likert scale)	[1, 5]	2.34	1.18
Home Rural	Whether a driver's home is located in a rural area (1 = Yes)	[0, 1]	0.18	0.38
Home Semi-Urban	Whether a driver's home is located in a semi-urban area (1 = Yes)	[0, 1]	0.18	0.39

before again conducting a Pearson correlation test on the resulting variable groups. After resolving any significant correlations, final OL models for diversion likelihood during morning and afternoon commutes were completed with 16 and 13 variables, respectively.

4- EMPIRICAL RESULTS & DISCUSSION

Table 2 shows the model estimation results for both the MNL and OL models. The pseudo R2 values for both models are considered as providing a satisfactory fit (McFadden, 1977), but the MNL model performs better than the OL model when comparing their pseudo R2 values. The following parameter interpretations and hypothesis discussions (in the next section) therefore focus on results from the MNL model.

4-1- Effects of Information-Seeking Behavior

The results of the multinomial logit models found significant relationships between several independent variables in each variable category for both morning and afternoon commutes. As expected, information-related variables produced noticeable effects on drivers' likelihood of diversion while commuting. During morning commutes, drivers who received information from the radio or TV sources or only seek information when encountering congestion were less likely to select No Divert, while those who rely on visual cues and direct observation were less likely to be Unsure about diverting. Conversely, those who were unsure about information or reported not seeking information were more likely to select No Divert. Drivers who only seek information before departure and those who were Unsure about disregarding information and taking their own route were more likely to be Unsure about diverting. Fewer effects of information-related variables were found during afternoon commutes, however each significant variable found that drivers were less likely to choose No Divert (drivers who seek information multiple times throughout a trip) or less likely to select Unsure (drivers who do not disregard information and those sourcing information from the web or direct observation). Due to these findings, hypothesis H1, which posits that drivers receiving information are more likely to divert than others, was not rejected in this study.

4-2- Effects of Disruption Type

Several disruption scenarios showed significant effects on diversion likelihood during commutes. Drivers who selected No Divert during work zones were more likely to select No Divert during both morning and afternoon commutes, while those who were Unsure about work zone diversion were also more likely to select Unsure during both morning and afternoon commutes. Those who reported being Unsure about their awareness of planned special events were more likely to select No Divert and Unsure during morning commutes, with the effect being stronger for Unsure drivers. Drivers who were Unsure about diverting during special events were also more likely to be Unsure about diverting during afternoon commutes. Those who selected No Divert during adverse weather events were more likely to select No Divert during morning commutes and were less likely to be Unsure about diversion during afternoon commutes. Finally, those who chose No Divert during incidents were more likely to choose No Divert during afternoon commutes. Due to these findings, hypothesis H2, which posits that drivers unlikely to divert during work zones and weather events are also less likely to divert during commute trips, was mostly supported in this study.

Table 2. Model Estimation Results

Variable	Multinomial Logit (MNL)								Ordinal Logit (OL)				Hypothesis
	No Divert				Unsure								
	AM Commute		PM Commute		AM Commute		PM Commute		AM Commute		PM Commute		
	Coeff	p-Value	Coeff	p-Value	Coeff	p-Value	Coeff	p-Value	Coeff	p-Value	Coeff	p-Value	
Constant_NO	1.05662 ***	0.0032	0.26748	0.4653	(na)				(na)				(na)
Constant_UNSURE	(na)				-1.21152 ***	0.0000	-0.65184 ***	0.0090	(na)				(na)
Travel Time Save (N)	1.07402 ***	0.0000	0.75213 ***	0.0029	(na)		0.65854 **	0.0216	-1.114 ***	< 0.001	-0.606 ***	0.002	(na)
Workzone (N)	0.64468 ***	0.0060	0.55603 **	0.0146	(na)				-0.604 ***	0.004	-0.674 ***	< 0.001	H2 (not fully rejected)
Weather (N)	0.44204 **	0.0161	(na)		(na)		-0.95846 ***	0.0000	(na)				H2 (not fully rejected)
Information (N)	0.98048 ***	0.0000	(na)		(na)				-0.818 ***	< 0.001	(na)		H1 (not fully rejected)
Information (U)	0.76500 ***	0.0031	(na)		(na)				-0.480 **	0.021	(na)		H1 (not fully rejected)
AM Delay	-0.08835 ***	0.0000	(na)		-0.02993 **	0.0196	(na)		0.059 ***	< 0.001	(na)		H3 (not rejected)
Return (N)	0.59567 **	0.0230	(na)		(na)		-0.95588 ***	0.0084	(na)				(na)
Smooth (N)	0.47270 **	0.0375	(na)		(na)				-0.393 **	0.049	(na)		(na)
Dist. to Dest. (U)	0.72837 ***	0.0027	(na)		0.94743 ***	0.0001	0.39341 *	0.0511	(na)				(na)
PSE Aware (U)	0.59859 **	0.0199	(na)		1.03502 ***	0.0001	(na)		(na)				(na)
Sit Time <15	-0.664	0.0002	(na)		(na)				0.530 ***	< 0.001	(na)		(na)

	15 ***												
Age 18-30	0.37404 *	0.0511	(na)		(na)		-0.48077 **	0.0289	-0.368 **	0.025	(na)		H5 (rejected)
Source Radio	-0.49755 **	0.0319	(na)		(na)				0.531 ***	0.005	(na)		H1 (not fully rejected)
Passenger (U)	-0.60327 **	0.0135	(na)		(na)		0.63890 ***	0.0060	0.511 **	0.010	(na)		(na)
Social (N)	-0.66759 **	0.0270	(na)		(na)				(na)				(na)
When Congestion	-0.39670 **	0.0375	(na)		(na)				(na)				H1 (not fully rejected)
Longer (N)	0.33672 *	0.0841	0.56444 ***	0.0090	(na)				-0.290 *	0.077	(na)		(na)
Source TV	-0.77884 *	0.0880	(na)		(na)				0.659 *	0.061	(na)		H1 (not fully rejected)
Sit Time <20	(na)		-0.59003 **	0.0156	(na)				(na)				(na)
Road Freeway	(na)		-0.48089 **	0.0160	(na)				(na)				(na)
Job Public	(na)		0.56557 ***	0.0055	(na)				(na)				(na)
Incident (U)	(na)		0.86752 ***	0.0007	(na)				(na)		-0.561 ***	0.006	(na)
Sure (N)	(na)		0.62433 **	0.0158	(na)				(na)				(na)
Sure (U)	(na)		0.75904 ***	0.0003	(na)				(na)		-0.466 ***	0.003	(na)
PM Delay	(na)		-0.10813 ***	0.0000	(na)		-0.02392 **	0.0129	(na)		0.071 ***	< 0.001	H3 (not rejected)
When Multiple	(na)		-0.55039 **	0.0148	(na)				(na)				H1 (not fully rejected)

Freeway (U)	(na)		-0.36969 *	0.0690	0.65511 ***	0.0005	(na)		(na)				H4 (rejected)
Low Income	(na)		-0.49713 ***	0.0074	0.36610 **	0.0496	(na)		(na)				H5 (rejected)
Home Semi-Urban	(na)		0.55608 **	0.0156	(na)				(na)				(na)
Travel Time Save (U)	(na)				0.42721 *	0.0568	(na)		-0.437 **	0.020	(na)		(na)
Workzone (U)	(na)				0.71708 ***	0.0006	0.51768 **	0.0151	(na)		-0.371 **	0.032	(na)
Options (N)	(na)				-0.48305 *	0.0848	(na)		(na)				(na)
My Way (U)	(na)				0.37640 *	0.0684	(na)		(na)				(na)
Source Visual	(na)				-0.34393 *	0.0753	-0.37623 *	0.0548	(na)				H1 (not fully rejected)
When Before	(na)				0.49250 **	0.0486	(na)		(na)				(na)
Prefer Familiar (U)	(na)				0.88509 **	0.0356	(na)		(na)				H4 (not rejected)
Congest (U)	(na)				0.56561 **	0.0209	(na)		(na)				H4 (not rejected)
Source Web	(na)				(na)		-2.29627 **	0.0320	(na)				H1 (not fully rejected)
Options (U)	(na)				(na)		0.78027 ***	0.0001	(na)				H4 (not rejected)
PSE (U)	(na)				(na)		0.63038 **	0.0152	(na)				(na)
My Way (N)	(na)				(na)		-0.44168 **	0.0185	(na)				(na)
Stops (U)	(na)				(na)		0.55760 ***	0.0073	(na)				H4 (not rejected)
Incident (N)	(na)				(na)				-0.760 **	0.039	(na)		(na)
Cancel (U)	(na)				(na)				-0.378 *	0.055	(na)		(na)

Number of Sources	(na)		(na)		(na)	0.138 **	0.040	(na)
Sit Time	(na)		(na)		(na)	-0.023 **	0.025	(na)
Outward	(na)		(na)		(na)	0.646 **	0.018	(na)
Dist. to Dest. (N)	(na)		(na)		(na)	-0.395 *	0.078	(na)
Adventurous (N)	(na)		(na)		(na)	-0.356 **	0.018	(na)
Travel Time Reliability (N)	(na)		(na)		(na)	0.854 *	0.084	(na)
Home Rural	(na)		(na)		(na)	0.375 **	0.047	(na)
Model's goodness-of-fit statistics	N = 810; pseudo R2 = 0.2087	N = 810; pseudo R2 = 0.2002	N = 810; pseudo R2 = 0.2087	N = 810; pseudo R2 = 0.2002	N = 810; pseudo R2 = 0.129	N = 810; pseudo R2 = 0.109		
(Note: 'na' means not applicable; * p < 0.1; ** p < 0.05; *** p < 0.01).								

4-3- Effects of Time-Related Factors

Travel time-related factors also played an important role in the multinomial models developed. Drivers who reported experiencing longer delays during morning commutes were less likely to select both No Divert and Unsure during morning commutes, with the effect being stronger for No Divert. Similarly, drivers who reported experiencing longer delays during afternoon commutes were less likely to select both No Divert and Unsure during afternoon commutes, with the effect being stronger for No Divert. Drivers only willing to experience delays of less than 15 minutes were less likely to select No Divert during morning commutes, however during afternoon commutes this was true of drivers only willing to experience less than 20 minutes of delay. Drivers who chose No Divert for Travel Time Savings were more likely to select No Divert during both morning and afternoon commutes, and these drivers were also less likely to choose Unsure during afternoon commutes, with the effect being stronger for No Divert. Additionally, those who were Unsure about Travel Time Save were more likely to be Unsure about diversion during morning commutes. Lastly, drivers who selected No Divert when offered alternate routes with longer travel times were more likely to select No Divert during both morning and afternoon commutes. Due to these findings, hypothesis H3, which posits that drivers who face longer delays during commute trips are more likely to divert during a typical commute trip, was not rejected in this study.

4-4- Effects of Trip-Related Factors

Several variables related to other trip characteristics were found to have significant relationships with commute diversion. Drivers who reported not returning to their original route after diverting were more likely to choose No Divert during morning commutes and were less likely to be Unsure during afternoon commutes. Those who were Unsure about diverting when farther from a destination were more likely to choose both No Divert and Unsure during morning commutes, with the effect being stronger for Unsure; these drivers were also more likely to be Unsure about diversion during afternoon commutes. Drivers who were Unsure if they drive differently when a passenger is present were both less likely to choose No Divert during morning commute and more likely to be Unsure about diversion during afternoon commutes. Drivers unsure about being more willing to divert when more rerouting options are available were less likely to be Unsure about diversion during morning commutes but more likely to be Unsure about diversion during afternoon commutes. Those who claimed to be Unsure about being more likely to divert to a freeway than a local street was more likely to be Unsure about diversion during morning commutes and less likely to choose No Divert during afternoon commutes. Additionally, drivers who typically use freeways during their commutes were less likely to select No Divert during afternoon commutes. Those who were unsure or disagreed about feeling confident in making the best choice when diverting was more likely to choose No Divert during afternoon commutes. Drivers who were Unsure about preferring familiar routes or if congestion was a problem during typical commutes were more likely to be unsure about diversion during morning commutes, while those unsure about the influence of the number of traffic lights along an alternate route on their likelihood of diversion were more likely to be Unsure about diversion during afternoon commutes. Finally, drivers who preferred shorter, congested routes to longer, smoothly flowing routes were more likely to select No Divert during morning commutes, while those who denied being more likely to divert if other drivers divert were less likely to select No Divert during morning commutes. Due to these findings, hypothesis H4, which posits that drivers who express uncertainty about the effects of trip-related factors are also more unsure about diversion decisions during commutes, was also not rejected in this study.

4-5- Effects of Demographic Characteristics

Demographic variables also showed significant relationships to the dependent variables investigated. Surprisingly, drivers between the ages of 18 and 30 were more likely to select No Divert during morning commutes and less likely to be Unsure about diversion during afternoon commutes. Drivers who reported an annual household income of less than $100,000 were more likely to be Unsure about diversion during morning commutes and less likely to select No Divert during afternoon commutes. Those with jobs in the public sector and those whose homes are located in semi-urban areas were found to be more likely to choose No Divert during afternoon commutes. Due to these findings, hypothesis H5, which posits that older drivers and those who earn a lower annual household income are less likely to divert than younger, higher-earning drivers, was also rejected in this study.

5- CONCLUSIONS

The findings of this research provide numerous insights into the routing and rerouting behavior of commuting drivers facing unexpected delays due to congestion caused by disruptions of coastal roak networks. As expected, the effects of seeking and receiving en-route information on traffic conditions and routing guidance seemed to be related to lower levels of uncertainty and a higher likelihood of diverting. However, the effects were related to sources such as radio, television, and website advisories as opposed to high-tech alternatives like in-vehicle navigation systems or smartphone applications like Google Maps or Waze. Results showing higher willingness to divert when facing longer delays were also expected, but the findings of this study make an important contribution to previous research on this topic. While other studies have shown that diversion likelihood increases with delay durations on specific trips, these findings suggest that drivers who typically encounter longer delays on certain types of trip are in general more likely to divert on that type of trip, not just on a specific trip with a specific amount of congestion. Unexpected findings included those related to demographic variables. It was expected that older drivers would be less willing to divert, whether due to habitual inertia or aversions to using routing technology; however, support for this claim was not found in this study. It was also expected that those earning higher incomes would be more willing to divert, perhaps due to a higher value of time or access to better information and technology; however, support for this claim was also not found in this study. What was highlighted throughout the analysis was the important role of uncertainty in diversion decision-making. These types of decisions are complex processes that drivers themselves may not fully understand. The wide variety of situations encountered during repeated trips such as commutes may make assigning a particular number to their diversion willingness difficult. Therefore, it was important to include this neutral option in the survey questionnaire, and this decision was validated by the multiple significant effects between drivers who reported being uncertain about a number of influential factors investigated in the study.

These findings could be useful for transportation officials and local authorities of coastal areas in a variety of practical applications to help with both short-term and long-term transportation planning problems. Understanding who will divert in which circumstances can aid in short-term traffic planning by informing authorities which alternative routes might experience an unexpected increase in traffic volumes, allowing for altered traffic signal timing plans to be implemented to accommodate the increased flow. It may also guide traffic agencies in crafting and disseminating the most appropriate and effective traffic advisories, for example on roadside variable message signs during disruptions to encourage a desired amount of diversion. In the long-term, understanding driver routing behavior becomes very important as the market penetration rate of automated and connected vehicles continues to rise. Using these findings to improve autonomous pathfinding algorithms can make driving in a mixed traffic environment as safe as possible by accurately mimicking human behavior.

This study is subject to certain limitations. Due to resource restrictions, the data collected are convenience samples, not truly random samples. Additionally, the definition of morning commutes denoting trips from home to work and afternoon commutes denoting trips from work to home may exclude any drivers who work evening or overnight shifts and commute at non-peak times. Future research could consider including additional factors (e.g., road amenities) in understanding drivers' en-route diversion choices. It would also be interesting to expand the study scope to find out how these factors would influence route diversion behavior of other coastal road users (e.g., transit riders, pedestrians, and bicyclists). More broadly, this study could be expanded to investigate how travel disruptions would influence route diversion, departure time, and/or mode choices jointly in considering the increasing investment on our transportation infrastructure (e.g., public transit, sidewalk, and bike lane). Deeper statistical analyses can provide enhanced insight into the driving behaviors being investigated. Based on these findings, future surveys could focus on the roles of autonomous vehicles or other factors in route choice behavior and examine them more deeply.

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