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Motivators and Preferences of Route Diversion During Roadway Incidents

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MOTIVATORS AND PREFERENCES OF ROUTE DIVERSION DURING ROADWAY INCIDENTS

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ABSTRACT

When confronted with congestion and delay, drivers often divert their route. Depending on factors like purpose, urgency, destination, route alternatives, type of disruption, and mode options, common diversionary options can range from changing departure time, route, and mode to canceling a trip altogether. One of the foundational building blocks of travel forecasting is traffic assignment, which is used to distribute trips over a network using complex algorithms to aggregately represent the desire of drivers to minimize travel time.

While these assignment models are backed by decades of research and observational experience, they are also limited by the fact that they do not account for the infinite number of factors and conditions that influence the routing of individual drivers. As the ability of transportation agencies to detect incidents and inform drivers of conditions has improved, there is increasing interest in knowing if drivers will divert and why.

This thesis describes results of research using marketing-based survey techniques to evaluate driver diversionary behavior during roadway incidents. The survey was used to identify and assess diversionary choice-making based on a) travel behaviors and habits, b) under routine and adverse conditions, c) for different incidents and route options; and d) under varied guidance information available to them.

Among the broad findings of the study that were consistent with prior research was the general preference of drivers to seek alternate routes around congestion and the importance they place on travel time as their primary motivator. Interestingly, younger males showed the lowest level of influence from guidance information, and route familiarity had a lower influence on diversionary routing among all groups, suggesting a higher level of trust and reliance in real-time mobile routing guidance than was originally anticipated in the beginning of the study. Another

interesting finding, not seen in prior research, was the high importance placed on route safety and the time of day, particularly for female drivers. While the study was not able to address why, fundamentally such relationships exist, these findings can be used to improve the predictive accuracy of trip routing and assignment forecasts, particularly under disrupted network conditions.

CHAPTER 1. INTRODUCTION

Drivers typically plan and carry out their travel to most effectively utilize their time. Travel delay, and the missed opportunities that result from it, are among the most frustrating issues for drivers. Broadly speaking, travel delay is generally categorized as either recurrent or non-recurrent. Recurrent congestion is most commonly associated with routine high-volume periods, like morning and evening workday commutes. Non-recurrent congestion is more varied, not only in its time and place, but in the ability to predict it. While many major planned events and adverse weather conditions can be anticipated, nonrecurrent congestion from traffic crashes and unexpected emergencies is difficult to pinpoint (Karaer et al., 2020).

One of the cornerstones of infrastructure planning is the need to assess the costs and benefits of capital investments. While costs can be computed in terms of physical components like material quantity, labor effort, right-of-way, and the like; benefit calculations tend to be more operationally focused; often using performance indicators like capacity, volume, travel time, speed, delay, and crashes. Traffic modeling provides highly effective means to quantify operational traffic performance. From network-wide forecasts of link volumes to intersection-specific assessments of capacity, queuing, and delay; modern state-of-the-practice modeling systems permit detailed estimates and assessments of performance under a range of infrastructure, driver, modal, and activity conditions. And, while traffic models continue to advance in predictive accuracy; computational speed and power, and level of quantitative fidelity, the complex mathematical descriptions of travel and trip making used by most models are based on travel time minimization formulae backed up by observational evidence. What these formulations do not incorporate, however, are explicit driver motivations, influencers, and preferences for the routing choices they make, particularly during disruptions.

A key part of forecasting traffic congestion is to understand driver trip making and traffic routing. The assignment of trips onto routes within networks is critically important because it can be used to show the benefits and costs of capital infrastructure investment and how travel patterns can change based on policy decisions, particularly in urban areas. Forecasting traffic patterns can be extraordinarily complex with many varying unknowns, however. The highly specialized field of transportation network modeling focuses on these challenges. Network analysts use complex models to represent and examine the movement of vehicles through networks of varying topological, control, volume, and capacity conditions. Through decades of research, a range of sophisticated techniques have been developed to forecast link traffic volume traffic based on the notion that drivers will seek out shortest travel time path while also tending to "spread themselves out evenly" across available routes such that no particular route would not be overwhelmed if logical near-by routes were available to relieve excess demand.

While drivers clearly seek to minimize travel time, there are also a near-infinite number of specific needs, conditions, constraints, and preferences that also come into play for individual drivers at different times and in different locations. One example is when drivers chain multiple destinations into a single trip, such as school drop offs and grocery shopping as part of a commute between work and home. Another occurs when drivers, particularly commuter drivers who are familiar with a network, seek ways to avoid recurrent and non-recurrent congestion. Experience and observation show that many drivers actively seek ways to avoid congestion. This may be accomplished by cancelling or delaying travel once congestion is apparent, departing earlier if they are aware of impending congestion, changing modes when available, or most commonly, seeking alternate routes of travel when their usual route is congested.

Not only does rerouting increase the efficiency of individual drivers, but it can also have the broader effect of improving the wider efficiency of entire transportation networks. By taking diversionary action, drivers distribute themselves more evenly on routes and exploit under-capacity routes to reduce the wider impact of individual link disruptions. Currently, however, relatively little is known about the factors and conditions of disruptive incidents and characteristics of individual drivers in terms of their motivation to divert to a different path, then, if they do, the relative importance of potential influencers on their choices.

The research described here sought to better understand aspects of potential preferences, motivators, and influencers of driver route selections. In the research, assumed travel conditions associated with different travel disruptions was compared to certain fundamental driver characteristics to determine if it was possible to understand first if, then why, drivers might divert their travel from one route to another less-congested route if the original route was slowed by a crash, work zone, or high-volume congestion. Of particular interest was to determine if relationships existed between expressed diversionary tendency and the age, gender, geographic region, and educational attainment of drivers. It was thought that a deeper understanding of driver preferences, influencers, and motivators, could ultimately improve the predictive accuracy of network routing and trip assignment forecasts under distributed network conditions.

Another interesting aspect of the work was the way in which travel-making decisions were identified. Driver decisions and preference choices were collected using on marketing-based surveys that have been applied for decades in business marketing fields to assess the likelihood of consumer choice based on purchasing habits. Here, however, preference and choice-making were assessed in terms of travel decision making by employing a five-point Likert scale to identify:

1. travel activities, travel-making preferences and attributes of drivers,

2. driver decision-making as it might be influenced by disruptive incidents on a route,

3. driver awareness of and opinions regarding the use real-time traffic guidance information, and

4. influential factors of driver diversionary behavior across different driver sociodemographic groups.

This thesis includes four main sections that summarize and highlight the primary components of the research. The first section is a brief review of the literature which focuses on driver diversionary decision-making under incident conditions and within interrupted networks. This is followed by a section that describes the data and methods that were used in this study. It also includes a description of the survey and the subject pool used to gather driver characteristic and preference data and how it was used in this research. In the section that follows, a discussion of the analytical testing that was performed on the data along with the findings from it is included. Finally, in the conclusion section, broader findings and implications are summarized as well as suggestions for the application of this new knowledge and suggestions for future work are offered.

CHAPTER 2. LITERATURE REVIEW

Among the unique aspects of the research were the leveraging of the distinctly different, yet overlapping, study techniques of traffic engineering and business marketing. In effect, the researchers used techniques common to researchers who study consumer purchasing choice behavior to evaluate influences on driver route diversion choice. Because of this it was necessary to review the findings of prior relevant research from several areas including decision-making differences between various demographic variables, common diversionary methods, methods of prior data collection and analysis (including surveys, simulators, sensors, and complex mathematical models) along with motivations for and execution of driver diversionary strategies. The sections that follow highlight and briefly summarize prior research to identify how identify how individuals differ in making decisions when analyzing specific demographics, how drivers react to traffic disruptions, the factors that influence their rerouting decisions and strategies; and how both individual and system-wide decisions can impact the overall efficiency of transportation networks.

2.1. Decision-Making Differences

A review of prior research showed that individual decision-making tactics differ within several demographic categories. The demographic variables analyzed include gender, age, education level, and area type (i.e., urbanized and non-urbanized areas). The findings are based on various methods of data collection, including surveys, simulators, and psychological analysis methods.

2.1.1. Between Genders

Prior study of the effect of gender differences, specifically between men and women, has consistently shown that men and women differ with respect to personality traits, information

processing, and decision-making. Numerous studies have established similar characteristics across men and women's behaviors due to their biological sex. In 1984, Hall analyzed a wide range of factors to determine consistent differences between gender, such as facial expression, body movement, locus of control, and aggression levels. She found that nonverbal gender differences could be explained by cultural expectations and social learning processes but could not be exclusively related to one reason.

Nearly a decade later, Feingold (1994) conducted a quantitative analysis of gender differences utilizing a meta-analytic methodology. Prior to this study, women were typically thought to conform to public opinion (Eagly, 1978) and to be more concerned with pleasing those around them (Miller, 1986). Feingold (1994) observed other characteristics that previous studies had not examined. The findings suggested that men were more assertive and had a higher self-esteem than women; however, women had higher levels in extraversion, anxiety, trust, and nurturance when compared to men. The study also presented that there were no significant differences between gender in social anxiety, impulsiveness, locus of control, and orderliness. Similarly, Meyers-Levy (1998) found that women tended to be concerned with others alongside themselves, while men tend to be more self-focused, self-assertive, and achievement oriented.

Additionally, Feingold (1994) proposed the biological, sociocultural, and biosocial models of gender differences. The biological model indicated that there are innate differences between males and females. Shors (2002) combined psychology and medicine and presented that there are significant differences in the anatomy of the brain between biological sex. In 2006, Kotulak expanded these findings to determine that a main explanation for the differences in the brain anatomy is the different hormones produced by men and women. These differences cause

men and women to experience emotional experiences, visual information, and auditory information differently (Cahill, 2005).

Feingold's (1994) sociocultural model demonstrated that behavioral common differences between gender are results from socially learned and accepted gender roles and expectations. In 1981, Bem observed the way in which individuals incorporate their self-identity to learned gender roles and expectations. The study determined that individuals match their behaviors to the stereotypical gender prototypes. Later, Palan (2001) focused on the degree to which individuals identify with masculine and feminine personality traits. The results indicated that specific gender roles and identities are more predictive of decision-making behaviors compared to biological sex.

The final model from Feingold's study in 1994 was a combination of the biological and sociocultural models, the biosocial model. The biosocial model illustrated that both biological and sociocultural aspects of individuals affected how they made decisions. Therefore, it was important to acknowledge both perspectives. Human behavior is responsive of both biological temperament and an individual's character, which is largely determined by the environmental norms (Schmidt et al., 2012).

In addition to the three models proposed in Feingold (1994), Meyers-Levy proposed a Selectivity Model to illustrate gender differences in advertising and consumer behavior areas in 1998. The model suggested that women are typically process information completely, while men tend to selectively process information. These findings are further analyzed in studies (Laroche et al., 2000; Cleveland et al., 2003) to reaffirm that women often acquire detailed information to make decision, while men tend to make decisions with a lower requirement of information details.

2.1.2. Between Ages

Prior study has also examined the effect of age on the adoption of various technologies; however, very little research has observed how age affects decision-making behaviors in general. In 1977, Phillips and Sternthal found that as people aged, they reduced their involvement with others and became much more narcissistic. Their research illustrated that older individuals demonstrated less conformity compared to their younger counterparts. Additionally, Phillips and Sternthal indicated that while there was a sharp decrease in suggestibility as individuals aged, there was a steady decline in persuasion.

Years later, John and Cole (1986) examined the limitations in the abilities to process information of young and elderly individuals. The data illustrated that age is independent to the ability to solve problems; older individuals were not always outperformed by the younger individuals in the study. In a later study, Yoon (1997) examined how individuals differed in the preferred types of information they received by age. She found that older individuals preferred a more simplistic form of the information to process, while younger individuals desired more detailed information prior to making a decision. Additionally, Yoon (1997) found that the time of the day affected how both groups, regardless of age, made decisions. She suggested that the optimal time of day is an important factor in decision-making because all individuals utilized detailed decision-making processes during the peak times of the day.

Prior study has also analyzed how age affected individuals’ willingness to adopt new advancements in technology. Czaja et al., (2006) found that older individuals were less likely to adopt new technology in their workplace, due to unfamiliarity with computers or computer anxiety. Similarly, Morris and Venkatesh (2003) found that older consumers relied more on the subjective norms of rejecting new technology in their workplace compared to younger

consumers. With regard to new technologies in transportation, there was a significant difference in the willingness to accept anything innovative between younger and older drivers. Abraham et al., (2017) completed an online survey to analyze drivers' inclination to using differing levels of automation. They found that older respondents expressed a willingness to use some level of automation but were extremely uninterested in ever utilized a fully autonomous vehicle, while younger drivers were more willing to use fully autonomous vehicles in the near future.

2.1.3. Between Education Levels

Researchers have also examined how the highest level of education obtained by individuals affects their methods in making decisions. In 1974, Huffman analyzed the role the education played in decision-making. He suggested that education contributed to increased production as an "allocative effect" as well as a "worker effect." He found that an increase in successful decision-making was positively related to an increase in the education of the farmers, which enforces the importance of knowledge of job details in the workplace.

Keller et al., (2007) analyzed whether education level affected ethical decision-making of accountants in the United States. The study suggested that there are differences in the ethical standards of individuals based on their educational level (i.e., graduate versus undergraduate). Individuals with a graduate-level education appeared to have a better understanding of the impact that every action had on other decisions.

Prior research related to how education affects health-related decisions suggested a different finding than Huffman (1974). Lupton (1997) found that individuals with a lower education level appeared to be more willing to accept health advice from their doctors due to a greater level of respect of their education. On the other hand, Lupton (1997) found that patients with a higher level of education were more likely to question the doctor on their advice.

Similarly, Baker et al., (1996) found that patients with lower literacy reports reported difficulties in asking health-related questions to their doctor and felt that their doctor did not listen or communicate clearly. Roter et al., (2007) suggested that consultations containing an extensive technical language was more problematic for patients with a lower education compared to those with a higher education. Complimentary to the previously studies mentioned, Levinson et al., (2005) performed a population-based survey to better understand how demographic variables, such as education level, influenced individuals' preferences for participation in decision-making. The study found that women with a higher education level were more likely to prefer an active role in decision-making compared to all other demographic combinations.

2.1.4. Between Area Types

Because of significant differences in the operational, developmental, control, and traffic volume characteristics, transportation systems are often segregated into urbanized and non-urbanized areas for analysis. Often, traffic in urban population centers is characterized by daily commuter peaks, shorter trip lengths, and a wider availability travel modes. With higher volumes, come additional environmental concerns, including air and water pollution and the consumption of fossil fuels. Cities are wide viewed in terms of their significant contributions to climate change compared to rural and suburban areas (Heinonen and Junnila, 2011). Several studies (Carney et al., 2009; Rauhala et al., 1997; Glaeser and Kahn, 2010) have contradicted this common belief and proven that carbon emissions in cities have been reported as substantially lower than surrounding non-urbanized areas. These findings potentially suggest that drivers in non-urbanized areas are more likely to utilize their vehicles more often than drivers in urbanized areas.

Driver behavior, especially with regard to safety, is another common difference between urbanized and non-urbanized areas. Eberhardt et al. (2001) found that the death rate from various causes in the United States is significantly higher in rural areas when compared to urbanized areas. Rakauskas et al. (2009) explains that despite only observing vehicular crash rates, non-urbanized areas maintain the higher fatality rate. Several researchers (Zwerling et al., 2005; Blatt and Furman, 1998) have analyzed why this phenomenon is so prevalent in rural areas and found that fatal rural crashes typically involve the following characteristics: more than one fatality per crash; younger driver; male driver; alcohol consumption; higher speeds; head-on collision; ejected person due to seatbelt non-compliance. Although these characteristics may also occur in urbanized crashes, there are other factors (i.e., design elements, medical personnel timing, psychological differences) in non-urbanized crashes that may explain the higher fatality crash rate.

Non-urbanized roads are typically designed to fit the nature of the surrounding areas. Blatt and Furman (1998) explained that majority of fatal crashes occur on high-speed two-lane highways that are typically located in rural areas. This potentially suggests that non-urbanized crashes may be a result of unsafe speeds for the present road conditions. Rural roads often incorporate more curvature than urban roads to accommodate for the natural state of the surroundings (Rakauskas et al., 2009). If drivers are not able to see the road curvature ahead of time, due to time of day or lack of attention, it may lead to a higher chance of getting in a crash. Crundall and Underwood (1998) observed the method in which drivers utilize visual information in different area types. The study found that less complex rural environments led drivers to adapt inappropriately to the roads, which ultimately led to more fatal crashes. Furthermore, Thiffault

and Bergeron (2003) observed that the reduction of visual clutter in rural areas can increase boredom in drivers, resulting in fatigue and lackadaisical visual scanning for hazards.

Prior research has shown that the higher fatal crash rate in non-urbanized areas could be a direct result of the length of time it takes medical personnel to arrive at a scene. Receiving medical treatment during the “golden hour” following any traumatic crash is crucial and increases the chances of survival (Champion et al., 1999). Due to decreased amount of medical care facilities in non-urbanized areas, when compared to urbanized areas, Svenson et al. (1996) found that the proximity to medical care seemed to be a significant factor for the outcome of fatal crashes. The results gathered by Champion et al. (1999) recorded that approximately thirty percent of emergency medical service crash responses in rural areas between 1993 and 1997 took over one hour, compared to less than eight percent for urban cases. Such delays in emergency medical service arrival times could potentially be the reason for the increased dead-at-scene rate in rural areas (Brown et al., 2000).

Additionally, several researchers have analyzed the potential for psychological differences between drivers in urbanized and non-urbanized areas, with regard to the perception of risk factors and safety interventions (Rakauskas et al., 2007). Blatt and Furman (1998) found that most rural crashes involve rural residents while most urban crashes involve urban residents. Furthermore, young male drivers, who are known to demonstrate risk-taking behaviors, are often involved in rural crashes (Rakauskas et al., 2009). Cox et al. (2017) explained that through grasping a better understanding of the attitudinal differences between drivers in urbanized and non-urbanized areas, transportation experts are able to develop interventions, such as education or enforcement programs, to better address each community individually. In turn, these

developments will assist in reducing the fatal crash rate in both area types and make transportation systems safer for all drivers.

Prior research also shows how metropolitan planning organizations plan ahead for the future of transportation and how urbanization of the area affects the way in which individuals make decisions demonstrates both the interest in and importance of assessing disruptive events, their resulting traffic conditions, and the effect of guidance information on driver diversionary behavior. Previous study has also demonstrated various emerging and improving methods of data collection and analysis so that while there are similarities between drivers in urbanized and non-urbanized areas, specific aspects of data reliability and assumption-making remain largely unexplored.

2.2. Influences on Diversion

A review of prior research showed that traveler diversion tactics typically fall into one of five major categories. The categories include elements that motivate route diversion, such as travel time, guidance information, perceived congestion levels, familiarity with the area, and trip purpose. The findings are based on several different methods of data collection and analysis, including surveys, simulators, sensors, and complex mathematical models.

2.2.1. Travel Time

Several studies in travel diversion research conclude that travel time is the most influential factor when drivers divert from a route. In a behavioral study using discrete choice models of diversion and return behavior, Khattak et al., (1993) proved that longer delays and longer travel times increased the probability of diversion. Similarly, Al-Deek et al., (2012) utilized a multinomial logit model to estimate and quantify the odds of selecting a diversion alternative over remaining on a current route. The results from the model showed that the most

prominent factors associated with greater route diversion were longer travel times and travel delays.

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. The results explained that the natural tendency to divert from a route increases when there is a higher than usual route travel time alongside shorter alternate route travel times nearby. Drivers who are naturally more precarious in their decisions are more likely to divert to avoid unexpected delays in travel time. Gan and Ye (2012) performed a behavioral study that focused on the urban freeway users of China. One of the main findings from the analyses completed was that travel time saving served as a positive factor in driver diversion. Although the prior two studies were completed in vastly different geographical locations, the most influential factor in route diversion remains the same, reduced travel time.

Gudishala et al., (2020) analyzed the differences in the level of congestion between a freeway in Baton Rouge, Louisiana and the level of congestion on surrounding local roads that triggers traffic to divert from the freeway. Due to prior emphasis on travel time importance in route diversion, the objective of the study was to measure the time lag between the onset of congestion and the diversionary behavior and relate it to a Travel Time Index. A Travel Time Index is defined as a "ratio of peak travel time to free-flow travel time". After completion of the analysis, the results indicate 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 a variance in time lag between traffic incidents. The results express rather high values in variance, such as 50 and 54, which indicates that diversionary behavior is not stable from incident to incident.

2.2.2. Guidance Information

Numerous research studies conclude that accurate traffic guidance information heavily influences driver diversionary behavior. In a behavioral study that manipulated route time changes due to inclement weather conditions, Khattak (1991) found that driver responses to unexpected travel conditions were often determined from traffic information. Real time traffic guidance information provides the basis for travel diversion decisions, therefore, the accuracy and timeliness of traffic information systems influences whether or not drivers alter their route. In a later study examining discrete choice models of diversion and return behavior, delay information gathered from radio traffic reports as opposed to observation of congestion increased the probability of diversion (Khattak et al., 1993). Due to the heavy reliance on traffic guidance information, the most important characteristic when designing Advanced Traveler Information Systems (ATIS) is that traffic information must be "customized" to account for individual preferences. These customizations should include the ability to select preferences for diversions, personalized route planning criteria (i.e., road types to seek out or avoid), display preferences (i.e., audio, map-based, text-based, or icon-based).

ATIS depends greatly on fully understanding drivers' route switching behaviors. Pal (1998) defines route diversion as a complex operation that is influenced by situational constraints, socioeconomic characteristics of motorists, and latent individual factors. One of the leading factors in travel behavior illustrated is that diversionary decision making relies on drivers having complete trust in the quality of provided guidance information. Choi and Choi (2008) performed a survey on drivers near Seoul, Korea. The results portray that drivers relied more on the provided traffic guidance information than his or her previously acquired knowledge of the

transportation network. ATIS is often blindly trusted when traffic disruptions occur on routes, especially during peak congestion time periods.

Khattak et al., (1995) examined the effect of traffic information on Chicago commuters' route changes to develop more reliable ATIS. The findings from the research show that the majority of the respondents, more than 60 percent, access, utilize, and respond to guidance information during their daily commute to work. Drivers often use travel information to lower their anxiety while driving, despite whether or not the guidance suggestions are used. Acquiring the overall knowledge of the traffic conditions helps drivers feel at ease when assessing the possibility of diversion.

Diversionary highway guide sign variables often influence drivers' abilities to process and interpret guidance information. Mast and Ballas (1976) manipulated message content, message severity, and message redundancy in traffic signs to observe changes in route choice, information interpretation time, and message preference. The results determined that higher severity messages and information regarding time delays were associated with diversionary decision making. As drivers were supplied with more congestion information and became more familiar with the messages, information interpretation time increased. This direct relationship indicated that travel diversionary choices were much easier with congestion information.

2.2.3. Perceived Congestion

A couple studies emphasized the importance of perceived congestion levels in route diversion. Xu et al., (2011) analyzed the most influential factors on driver diversionary behavior via a probit model in Shanghai, China. The results from the model were then compared to a stated preference survey to confirm the accuracy of the model. The results from the study explained numerous factors that influence driver diversionary behavior, including the importance

of visibility of congestion on the route ahead. Drivers often rely on observing downstream congestion to persuade their decision to either remain on their current route or divert to an alternate route and avoid delays.

Khoo and Asitha (2016) observed drivers' likeliness to alter prior travel decisions upon viewing traffic congestion levels on the route. The results from the study indicated that drivers were more sensitive to changes in density rather than speed when perceiving traffic congestion levels. Thus, a dynamic relationship between drivers' travel decisions and their perceived congestion levels is proposed. The relationship illustrates the typical changes in travel tactics under varying traffic conditions. The dynamic relationship is then observed in a travel demand model to indicate drivers most frequently utilized travel plan changes. The model shows that drivers typically perceive three congestion levels (i.e., low, medium, and high). Khoo and Asitha (2016) reveal that the likelihood to divert from a route is directly related with perceived congestion levels. Drivers typically delayed their departure time at a medium perceived congestion level, however, they were more likely to cancel their trip when a heavy congest level was detected on the route.

2.2.4. Familiarity with Area

A few researchers have proposed the influential relationship between familiarity with the area and driver diversionary behaviors. Richards et al., (1978) observed different field studies of point diversion of freeway traffic going to special events at the Fair Park complex in Dallas. Through a series of survey questionnaires, the data indicated that driver familiarity with the route and driver anticipation of the conditions on the alternate route have the most substantial influence on diversionary behavior. When drivers are familiar and confident with the areas where

their trip occurs, they are more inclined to use an alternate route to save delays in travel time without assistance from guidance information.

Khattak et al., (1994) observed commuters in the San Francisco Bay Area during their daily trips to and from work. The findings show that about 40 percent of commuters were estimated to change their route to or from work to avoid travel delays. It should be noted that drivers with a larger knowledge of the alternate routes in the transportation network and increased diversion opportunities were more likely to divert. In a later study observing daily commuters from Chicago and the San Francisco Bay Area, Khattak and Khattak (1998) recognized a direct relationship to diversionary behavior and duration of residency in the area. The results portrayed that the longer the duration of residency, the higher the natural tendency to discover alternate routes that avoid routine congestion. Once drivers became more comfortable in the area, they were able to increase their spatial knowledge of the transportation network to increase their overall efficiency in travel.

2.2.5. Trip Purpose

A likely influential and motivational consideration in diversionary decision-making for many drivers is trip purpose. Several researchers have explored this idea. An et al., (2021) found that drivers regularly undertook travel with various levels of time-space variability. Another early study by Jones (1977) found that drivers had much more flexibility in allocating time and selecting locations when completing discretionary activities versus obligatory ones. Later, in 1978, Ås categorized trips into four main purposes: activities in necessary time, contracted time, committed time, and free time. Activities in necessary time are made to satisfy physiological needs, which typically require little travel. The majority of travel demand derives from the need to participate in activities in contracted, committed, and free time. Contracted time refers to the

time given for paid work. Ellder (2014) explained that the activities in contracted time often have strong fixed-space constraints. Shen et al., (2013) explained that contracted time typically has larger fluctuations in time use, due to the potential for variations in departure times and working hours. Reinseth et al., (2012) defined committed time as the activities that individuals are bound to others through promise, such as household responsibilities. Schenk et al., (2007) described committed time activities as having a more flexible time budget than those conducted in contracted time, since they can be undertaken by other household members or be postponed. Lee and McNally (2003) defined free time as the time spent away from the aforementioned activities. Free time can be planned or completed spontaneously. Given the multiplicity of free time activities, people have a greater opportunity to visit various locations; therefore, free time activities were considered the least bound by time or space.

2.3. Data Collection Methods

The review of previous literature displays the variety and diversity of data collection methods utilized in driver diversionary behavior studies. In general, there are three main categories of data collection techniques, survey questionnaires, driving simulators, and roadway sensors. The findings from prior research describe the range within the different data collection approaches.

2.3.1. Surveys

Several studies in travel diversion research conclude that behavioral survey questionnaires are the most effective method in collecting data on diversionary behavior during travel. In 1978, Richards et al. examined the effectiveness of diversionary signing techniques via mail-back surveys that supplied comprehensive origin-destination data. The surveys were distributed to all drivers, regardless of whether or not they chose to divert from their route. The

results of the questionnaires supplied feedback on driver attitudes and reactions to point-diversion signing systems, allowed exploration in driver behavior trends related to diversion, and identified which factors were the most influential during diversion decision making.

Khattak often utilized survey questionnaires to obtain data in his studies. Khattak (1991) used mail-back surveys to test influential factors on diversionary behavior of downtown Chicago commuters during the morning peak period. In a later study, Khattak et al., (1994) employed a survey to explore the user benefits of ATIS in San Francisco Bay Area commuters. After analyzing the two datasets, Khattak et al., (1995) performed a comparison study between Chicago and San Francisco Bay Area commuters during the morning peak period. The comparison study used a similar survey questionnaire to evaluate the effect of traffic guidance information on travelers' route choice in efforts to better ATIS future developments. Through a further comparison analysis of the Chicago and San Francisco Bay Area commuters, Khattak and Khattak (1998) examined the effects of drivers' spatial knowledge on diversion responses to unexpected delay information via mail-back surveys.

A decade later, Khattak et al., (2008) utilized a comprehensive behavioral data set retrieved from the survey questionnaires in the Research Triangle area of North Carolina. The survey focused on largely public-sector delivery mechanisms to review the status of current ATIS technologies and to understand how travelers access and respond to the guidance information from the systems. The results of the survey hoped to answer whether an increase in guidance information knowledge is associated with an increase in the likelihood of travel diversion, as well as which forms of guidance information were the most influential in driver diversionary behavior.

Several studies include traffic guidance information as an extremely influential factor in diversionary behavior. Choi and Choi (2008) conducted an in-person survey questionnaire at eight separate tollgate locations throughout Seoul, Korea. The various survey locations were places that normally experience high rates of congestion but also have well-known alternate route choices available. Another on-site survey questionnaire was completed in China to explore diversionary driver responses to guidance information. Gan and Ye (2012) created a state preference survey questionnaire to observe how guidance information that supplied travel times on both urban freeways and local streets influences drivers to divert from their current route.

Khoo and Asitha (2016) completed two research studies that utilized survey questionnaires. The first study used two separate stated preference questionnaires in major spots of the Klang Valley region of Malaysia. During the survey, drivers were shown various scenarios that might appear on a cellular application that provides guidance information. The objective of the survey was to evaluate the impact of traffic guidance applications on drivers' decisions in route choice, alongside investigating which features on the application contribute to a higher use. In a second study, Khoo and Asitha (2016) utilize a survey questionnaire to collect travelers' overall opinions on traffic guidance applications. Traffic image applications are currently being developed to allow drivers to obtain real-time traffic congestion information via images mounted along the roadways. The images are captured through Closed Circuit Television Cameras that constantly update travelers on the most current road conditions. Ideally, this would allow drivers to carry out their trips in the most efficient manner, while avoiding any travel time delays. The goal of the survey was to analyze various traffic image applications to see how it may influence driver travel choices.

Another common type of survey questionnaires are telephone interviews. Al-Deek et al., (2012) utilized a Computer Aided Telephone Interview to conduct a survey in the Central Florida region. The survey analyzed how travelers perceive dynamic message signs to obtain traffic guidance information. Respondents were questioned on their current knowledge of where dynamic message signs were on the main toll roads in the transportation network area and how satisfied they were with the traffic guidance information that was supplied by the signs. Additionally, the survey questionnaire inquired how drivers believe they would divert in various situations to analyze stated preferences versus revealed preferences of the drivers.

2.3.2. Simulators

A few research studies conclude that data can be collected through driving simulators to observe diversionary behavior during travel. Mast and Ballas (1976) utilized an instrumental vehicle with an in-vehicle sign simulation device to collect habits of travelers. The objective of the study was to observe the influence of diversionary highway guidance signs on drivers' abilities to understand directional information. Alongside directional guidance information, the simulator supplied congestion information to drivers to assist in diversionary behavior in efforts to decrease travel delays. Xiong and Zhang (2013) paired a laboratory driving simulator with field Bluetooth detectors to model route changing decisions of travelers. The study collected behavioral data from the participants while mimicking typical driving conditions on Interstate-95 and Interstate-895 in Maryland. The conditions ranged from free flow speed to heavy congestion to observe how the participants reacted and whether or not drivers chose to divert to avoid delays.

Bonsall (1992) incorporated an Interactive Route Choice Simulator (IGOR) in the research study to examine the importance of traffic guidance information on route choice.

Although previous literature reveals the importance of guidance information in diversionary decision making, the results from this study suggest that users are hesitant to follow advice unless they find it convincing, and the more familiar they are with the network, the less likely they are to accept advice. The results portray that driver compliance to guidance information greatly depends on the quality and accuracy of the guidance, as well as the drivers' familiarity with the network.

2.3.3. Sensors

Although the majority of research studies concerning human behavior use data collection methods that retrieve information directly from the source, human behavior can be observed without direct communication. An example of an indirect data collection method that examines human behavior is roadway sensors. Gudishala et al., (2020) utilized roadway sensors to analyze the differences in the level of congestion between a freeway in Baton Rouge, Louisiana and the level of congestion on surrounding local roads that triggers traffic to divert from the freeway. A Bluetooth Detection System was installed along a section of Interstate-10 to detect congestion levels and diversion rates. Unfortunately, due to limited funding, only eleven sensors were installed throughout the road network. A few incidents were not fully observed due to a lack of devices where diversionary behavior occurred. Although roadway sensors allow revealed preferences to be naturally observed, they are often extremely expensive as well as tedious and time consuming.

2.4. Data Analysis Methods

The review of previous literature shows various data analysis methods utilized in driver diversionary behavior studies. In general, the majority of research manipulates mathematical

models to analyze the data that was previously collected. The findings from prior research describe different analysis methods to analyze driver diversion tactics.

Khattak et al., (1993) used discrete choice modeling to analyze trip factors that increase diversion probability. Discrete choice models are typically utilized to explain or predict a choice from a set of two or more mutually exclusive alternatives. The results from the discrete choice model indicated various influential factors in driver diversionary behavior, alongside recommendations to better design ATIS to increase overall efficiency in the transportation network. Choi (2011) incorporated a discriminant model to observe route diversion as a result of traffic conditions of roads and guidance information. Discriminant modeling is generally used to classify information by determining decision boundaries for the dataset. The study further examined the results of the discriminant model through Classification and Regression Trees (CART). CART is often used in data analysis to meaningful and natural levels within the results. Once a thorough discriminant analysis was completed, a discriminant model equation was proposed to predict route change for drivers.

Xiong and Zhang (2013) apply a Bayesian approach for modeling behavioral data of traveler diversionary behavior. Bayesian modeling represents uncertainty within the model through probabilities. Bayesian models distribute unobserved, or future, data when given the observed data. The models are based on assumptions of imperfect rationality of travelers. The models also assume that the independent variables must be statistically independent from each other. After the Bayesian model analyzed the data collected from a driving simulator, the model was calibrated for Maryland via the data collected from the Bluetooth detectors. Calibrating the Bayesian model to the particular sample pool allows researchers to transfer the original model to other geographical locations.

Al-Deek et al., (2012) applied a Multinomial Logit model to quantify the odds of drivers choosing an alternate route over remaining on their current route. Multinomial Logit models are typically used to predict the categorical placement of a variable within a dataset. Multinomial Logit models observe multiple independent variables to one dependent variable. Since the Multinomial Logit model is a form of a regression model, it is assumed that there is no need for the independent variables to be statistically independent from each other, which is unlike the Bayesian approach model.

Another common mathematical model utilized in statistical data analysis is the Probit model. Probit models are a type of regression model where the dependent variable can only be a binary variable, meaning it can only take two values. Xu et al., (2011) used a Corresponding Probit model to analyze the impact of the content of traffic guidance information and other influential diversionary factors on drivers in Shanghai, China. Corresponding Probit models are typically used to display a significant relationship between various categories. Gan and Ye (2012) incorporated a Cross-sectional Binary Probit model alongside a Panel Binary Probit model to identify which factors in dynamic variable message signs influence diversionary behavior. A Cross-sectional Binary Probit model is used to analyze a dataset at a fixed point in time. Panel Binary Probit models are utilized in datasets that contain multiple observations of each sampling unit. Through the dual usage of the two Binary Probit models, the results were able to be compared to one another to validate the models. The findings showed that the Panel Binary Probit model provides more robust statistical inferences for model coefficients when compared to the Cross-sectional Binary Probit model. The Panel Binary Probit model did not provide substantially different model coefficients for the data. Additionally, the t-test values for the Cross-sectional Binary Probit model were not accurate. The values regarding variables that

changed between drivers, such as the demographic characteristics, were overestimated, while the variables that changed between scenarios, such as travel time, were underestimated.

2.5. Summary of Findings and Conclusions

The review of prior research into differences in decision-making between various demographic categories, influential factors on diversionary behaviors, data collection methods, and data analysis methods demonstrates both the interest in and importance of assessing disruptive events, their resulting traffic conditions, and the effect of guidance information on driver diversionary behavior. Previous research has also identified ways to improve data collection and analysis so that, while there are common influential factors on diversionary behavior and traffic guidance information, specific aspects of data reliability and assumption-making remain largely unexplored. Thus, little is known about what motivates and influences drivers to divert to alternate routes when incident-related non-recurrent congestion occurs. To address this gap in knowledge the study described below sought to evaluate travel habits and preferences, driving habits, and opinions regarding real-time traffic guidance information of drivers to better understand, anticipate, and plan for such conditions.

CHAPTER 3. METHODOLOGY

The research was conducted using an online survey created to identify factors that were assumed to influence the decision of drivers to take an alternate path of travel during disruptive incidents. Prior to this survey, several "mini" pre-test surveys were also conducted to identify potential motivators and trends that could influence the study. Ultimately, the survey used here included a range of questions targeted at potential motivational factors that could influence their:

1. decision of whether to divert or not,
2. preference for specific route based on the characteristics or conditions that might be encountered on it, and
3. preference and use of available information used to guide them on their alternative route.

The focus of this thesis is only on issue #2 above; route preference based on influential factors of importance to individual drivers.

Although it is recognized that there are a near-infinite number of potential factors that could affect driver response along with an equally infinite number of decisions that any driver might make under a specific set of conditions, the survey was crafted to focus on driver decision-making at both broad and specific levels. A total of fifty questions were posed to test subjects. Most questions were measured on 5-point Likert scales anchored by "strongly disagree" and "strongly agree" with a "3" serving as the midrange neutral point. The Likert scale is a commonly used scale in the social sciences, psychology, statistics, business and marketing to score perceived and experienced "feelings" and "intensity" of respondents in a quantitative form. Another of its utilities is that it can be used to show statistical variation among subgroups in survey pool. This thesis focuses on the path preference portion of the research and, more specifically, the selection of a route as a function of age and gender.

3.1. Survey Questionnaire

The survey questionnaire was developed in Qualtrics™, a web-based survey tool, then presented to a pool of online survey participants. The survey questions were purposefully formulated, arranged, and presented to evaluate subjects to assess decisions in four categories to:

1. Examine their general travel habits under various routine and adverse conditions;
2. Assess their driving behaviors especially as they relate to various disruptive conditions and available routes;
3. Evaluate their awareness of, opinions on, and familiarity with various forms of traffic guidance and information;
4. Identify their relevant demographic characteristics.

The survey began with an introduction section explaining the objective of the project. Respondents were then asked to read the potential harms, benefits, and confidentiality statements before fully agreeing to participate in the survey. The Institutional Review Board approval number was included at the end of the introduction section to ensure all participants were informed properly. Once respondents selected that they had read and agreed to the aforementioned instructions, the fundamental survey began.

The first section focused on the current travel habits and preferences of the drivers. The first series of questions in this section inquired how often respondents visited destinations, such as work, school, the gym, shopping, and any recreational event, on a scale that ranged from visiting daily to never visiting the location. The second question in this section asked how willing drivers were to complete trips during certain inclement weather conditions, such as heavy rain, wind, fog, snow, or ice, on a 5-point Likert scale anchored by “strongly disagree” and “strongly agree” with a “3” serving as the midrange neutral point.

The next section included a behavioral scale, common in marketing-based research, that focused on decision-making confidence of drivers. All questions in this section utilized 5-point

Likert scales anchored by “strongly disagree” and “strongly agree” with a “3” serving as the midrange neutral point. The first question analyzed how confident participants felt in making diversionary travel decisions. The second question examined the level of difficultly respondents had making diversionary travel decisions. The final question in the section analyzed how often drivers felt that they made smart diversion behaviors when driving.

The third section centralized on present driving habits of the respondent. All questions in this section utilized 5-point Likert scales anchored by “strongly disagree” and “strongly agree” with a “3” serving as the midrange neutral point. The first series of questions in this section observed the likelihood of drivers to divert from a route when encountering various driving disruptions. The disruptions analyzed included crashes on the shoulder, crashes blocking one lane, crashes blocking all but one lane, construction work zones, and rush hour traffic. The second series of questions in the section examined the likelihood of drivers to divert from a route when encountering various road designs. The road designs considered included four-way intersections with traffic control devices, four-way intersections with no traffic control devices, roundabout or traffic circles, freeways, and active school zones. The final series of questions in the section focused on the importance of several factors on influencing whether they may divert from a route. The factors analyzed were travel time, route length, safety of surroundings, time of day, and familiarity with the area.

The fourth section included another behavioral scale, common in marketing-based research, that focused on decision-making avoidance of drivers. All questions in this section utilized 5-point Likert scales anchored by “strongly disagree” and “strongly agree” with a “3” serving as the midrange neutral point. The first question analyzed how often participants avoid situations that require diversionary travel decisions. The second question examined the

preference level of respondents in making decisions related to travel diversion. The final question in the section analyzed whether drivers enjoy contemplating issues involving diversionary travel decisions.

The next section focused on opinions regarding real-time traffic guidance information. All questions, with exception to the last question, in this section utilized 5-point Likert scales anchored by “strongly disagree” and “strongly agree” with a “3” serving as the midrange neutral point. The first series of questions in the section examined the likelihood of drivers utilizing guidance information during recurring and non-recurring trips. The next question examined whether drivers would follow traffic guidance information if they were notified of a traffic disruption in advance. The next series of questions in the section observed the means in which participants access real-time traffic guidance information. The means observed included the radio, Department of Transportation, digital road signs, in-vehicle guidance assistance, and a cellular application. The final question in the section asked respondents to rate commonly used cellular applications in traffic guidance (i.e., WAZE, Apple Maps, Google Maps, Map Quest) in order of usefulness from one to four, where one is the most useful and four is the least useful.

The sixth section included another behavioral scale, common in marketing-based research, that focused on the pressure to finish of participants. All questions in this section utilized 5-point Likert scales anchored by “strongly disagree” and “strongly agree” with a “3” serving as the midrange neutral point. The first question analyzed whether drivers felt under pressure to finish travel quickly. The second question observed whether participants felt that they were expected to arrive at destinations as fast as possible. The final question in the section examined whether respondents felt that they needed to increase the speed of their travel to reach destinations in less time.

The final section of the survey gathered demographic information on the respondents. Each respondent was asked about the gender, age, marital status, highest level of education completed, current employment status, and current regional location. Due to the anonymity of the survey, respondents were able to answer the demographic questions truthfully to help in analyzing a relationship between demographics and diversionary behavior in drivers.

In addition to respondents answering the questionnaire, Qualtrics™ examines the latitude and longitude of where the survey was completed for each participant. The data was transferred into ArcGIS Pro™ to observe the spread of the dataset across the United States. ArcGIS Pro™ is a full-featured professional desktop GIS application that allows researchers to visualize and analyze data in 2D maps or 3D scenes.

The survey questionnaire was distributed via Amazon MTurk™ to retrieve responses from adults, over the age of eighteen, with car insurance, across the United States. Amazon MTurk™ is an online platform that connects businesses and consumers for various surveys and data analyses. As a cost-efficient way to survey a diverse group of respondents in an accelerated period, it was also ideally suited in conducting this research.

In the field of management, the use of online panel data has grown rapidly over the past decade, serving as the basis of just two studies in top management journals in 2006 to 214 in 2017 (Porter et al., 2019). Online panel data, in general, has been called "one of the most significant sampling developments in modern science" (Porter et al., 2019, p. 320). Amazon MTurk™, specifically, is a fundamental tool for conducting online surveys. It is, by a wide margin, the most popular online data collection platform survey platform, accounting for 66 percent of all survey studies using online methods. In a meta-analysis, Walter et al. (2019) also

concluded that online panel data yields substantially comparable results (effect sizes) with traditional data collection techniques.

3.2. Measures of Dependent Variables

This thesis analyzes two sets of dependent variables within the survey sample dataset. The first set of dependent variables analyzed influential factors on diversionary behavior. Previous driver behavior studies used observations of one or two influential factors on route diversion at a time. To advance the understanding of influences of diversions in traffic disruptions in this research, five dependent variables were selected for study, including:

1. travel time,
2. length of the alternate route,
3. perceived "safety and security" for drivers in the area of an alternate route,
4. time of day; and
5. familiarity with the area along an alternate route.

Assessment of driver importance to these conditions was made using a five-point Likert Scale, with responses that ranged from "strongly agree" to "strongly disagree." Questions posed to the subject were also created to be as simple and unambiguous as possible using the following statements:

- "Travel time is an important factor in whether I divert from a route during a trip,"
- "The length of the route is not an important factor in whether I divert from a route during a trip," (reverse scaled),
- "The safety of the surroundings is an important factor in whether I divert from a route during a trip,"
- "The time of day is an important factor in whether I divert from a route during a trip," and
- "My familiarity with the area is not an important factor in whether I divert from a route during a trip," (reverse scaled).

Additionally, prior research utilized observations of one or two disruption types to observe the effects on route diversion. To advance the understanding of influences of diversions in diversion severity in this research, five dependent variables were selected for study, including:

1. a crash on the shoulder of the road,
2. a crash blocking one lane of a multi-lane road,
3. a crash blocking all but one lane of a multi-lane road,
4. a construction work zone; and
5. rush hour traffic.

Similarly, assessment of driver importance to these conditions was made using a five-point Likert Scale, with responses that ranged from “strongly agree” to “strongly disagree.” Questions posed to the subject were also created to be as simple and unambiguous as possible using the following statements:

- “I use an alternate route when I encounter a traffic accident on the shoulder of the road,”
- “I do not use an alternate route when I encounter a traffic accident that blocks one lane of a multi-lane road,” (reverse scaled),
- “I use an alternate route when I encounter a traffic accident that blocks all but one lane of a multi-lane road,”
- “I use an alternate route when I encounter a construction work zone,” and
- “I do not use an alternate route when I encounter rush hour traffic,” (reverse scaled).

3.3. Measures of Independent Variables

Responses to the independent variable survey questions were analyzed across four demographic variables, gender, age, education level, area type. In this thesis, “area type” is used to define the distinction between urbanized and non-urbanized areas. These categories were used because of their potential to illustrate differences in driving behaviors and characteristics among

key driving population groups of interest in the research. In particular, the research sought to examine often-cited stereotypes in the way men and women, of all age groups, education levels, and area types make decisions and respond to route guidance while driving.

3.3.1. Gender

All participants were asked their gender in the survey questionnaire. Five gender designations were available for selection including male, female, transgender, non-binary, and "prefer not to answer." Only five of 1,012 participants, or 0.5 percent, selected transgender, non-binary, or prefer not to answer. Individuals that selected either of these categories were eliminated from analysis due to insufficient sample size. The remaining participants remained categorized as male or female.

3.3.2. Age

Respondents were next asked to select which age group best described themselves. There were six age group categories available for selection including: 18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64; and 65 or older. The age categories are commonly used in business-marketing because they generally classify relatively similar groupings of activities and habits. To simplify analysis, the sample groups were aggregated into groups of "young" and "old." Participants that chose ages 18 to 34 were categorized as "younger drivers," while those that selected ages 35 or greater were categorized as "older drivers."

3.3.3. Education Level

All participants were asked their highest level of education in the survey questionnaire. Seven gender designations were available for selection including: less than high school, high school graduate, some college, 2-year degree, 4-year degree, professional degree; and doctorate. Only 21 of 1,012 participants, or 2.08 percent, selected less than high school or high school

graduate. Individuals that selected either of these categories were eliminated from analysis due to insufficient sample size. To simplify analysis, the sample groups were separated into groups of varying education levels. Participants that chose “some college” or “2-year degree” were grouped in the lowest of the education levels. Individuals that selected “4-year degree” remained separate and ranked in the middle of the education levels. Participants that chose “professional degree” or “doctorate” were grouped in the highest of the education levels.

3.3.4. Area Type

All participants were asked to describe which geographic region described where they currently resided in best in the survey questionnaire. Six geographic regions were available for selection including: Pacific, Rocky Mountain, Mid-West, Southwest, Southeast; and Northeast. In addition to asking respondents to select their location, the data was transferred into ArcGIS Pro™ to observe the spread of the dataset across the United States. Each datapoint was then cross compared to their response to the question regarding geographic region. If the location given off of the latitude and longitude did not match the response to the geographic region, the datapoint was removed to ensure accuracy in the sample. To simplify the analysis, the remaining sample groups were then classified as either urban or non-urban based on their location pinpoint. Per the definition provided by the United States Department of Transportation (USDOT) Metropolitan Planning Organization (MPO), an “urbanized area” is classified as an area populated by 50,000 people of more. The USDOT MPO definition is the most widely accepted definition of urban versus non-urban areas (Johnston 2004). This thesis will further refer to the distinction between urban or non-urban as area type.

3.4. Sample Size and Characteristics

The total sample size for the dataset was 1,012 responses. The survey data was analyzed in various ways to determine how certain demographic characteristics affected diversionary driver behavior. The subgroupings within the dataset varied in sample size due to the restrictions on the demographic variables. There were five subgroups of the dataset:

- Subgroup A
- Subgroup B
- Subgroup C
- Subgroup D
- Subgroup E

Subgroup A observed gender and age, which included 1,007 usable responses. There was a decrease in sample size because participants that selected transgender, non-binary, or prefer not to answer were eliminated from analysis due to insufficient sample size. The sample was approximately 54.7 (n = 551) percent male and 45.3 percent female (n = 456). Similarly, the sample was split nearly in half by age with 54.7 percent (n = 551) classified as "younger drivers" (ages 18 to 34) and 45.3 percent (n = 456) as "older drivers" (ages 35 and greater).

Subgroup B analyzed gender, age, and education level, which included 991 usable responses. There was a decrease in sample size because participants that selected less than high school or high school graduate were eliminated from analysis due to insufficient sample size. The sample was approximately 54.7 (n = 542) percent male and 45.3 percent female (n = 449). Similarly, the sample was split nearly in half by age with 54.8 percent (n = 543) classified as "younger drivers" (ages 18 to 34) and 45.2 percent (n = 448) as "older drivers" (ages 35 and greater). Additionally, the sample was divided into three education levels. The lowest level

consisted of participants that selected “some college” or “2-year degree”. The middle category was for individuals that completed a 4-year degree. The highest education level was for those who chose “professional degree” and “doctorate.” The sample was approximately 8.9 (n = 88) percent in the lower category, 70.9 (n = 703) percent in the middle category, and 20.2 (n = 200) percent in the highest category.

Subgroup C observed area type, which included 275 usable responses. There was a decrease in sample size because participants whose location given off of the latitude and longitude did not match their response to the geographic region were eliminated from analysis to ensure accuracy in the sample. The sample was approximately 56.7 (n = 156) percent urban and 43.3 (n = 119) percent non-urban.

Subgroup D analyzed area type and education level, which included 264 responses. There was a decrease in sample size because participants whose location given off of the latitude and longitude did not match their response to the geographic region, as well as if they selected less than high school or high school graduate were eliminated from analysis due to insufficient sample size and to ensure accuracy in the sample. The sample was approximately 58.0 (n = 153) percent urban and 42.0 (n = 111) percent non-urban. Additionally, the sample was divided into three education levels. The lowest level consisted of participants that selected “some college” or “2-year degree”. The middle category was for individuals that completed a 4-year degree. The highest education level was for those who chose “professional degree” and “doctorate”. The sample was approximately 15.2 (n = 40) percent in the lower category, 68.2 (n = 180) percent in the middle category, and 16.7 (n = 44) percent in the highest category. The final subgroup analyzed area type and gender.

Subgroup E included 272 usable responses. There was a decrease in sample size because participants whose location given off of the latitude and longitude did not match their response to the geographic region, as well as if they selected transgender, non-binary, or prefer not to answer were eliminated from analysis due to insufficient sample size and to ensure accuracy in the sample. The sample was approximately 56.6 (n = 154) percent urban and 43.4 percent non-urban (n = 118). Similarly, the sample was split by gender with 54.4 (n = 148) percent male and 45.6 (n = 124) percent female.

The goal was to acquire reliable data from this research project. Therefore, as an incentive, participants were paid $1.25, contingent upon approval of a valid survey. Using another common business marketing technique, two additional survey questions were included to track whether participants were paying adequately close attention to the survey. The two questions were arranged in the questionnaire form at strategic locations and stated the following: “Please select somewhat agree for this question” and “Please select strongly disagree for this question.” Respondents were rejected automatically if either of the two questions were incorrect. Surveys completed in less than two minutes were also rejected because they were deemed to be unreliable based on practical limits of comprehension and response.

CHAPTER 4. RESULTS AND DISCUSSION

The survey data was analyzed in five subgroups to observe the effects of various combinations of demographic groups on driver diversionary behavior. This chapter presents the results of the five subgroups. Subgroups A, C, D, and E observe how different factors (i.e., travel time, route length, safety of surroundings, time of day, and familiarity with the area) influence drivers of varying demographics to divert when they encounter a traffic disruption. Subgroup B examines how different levels of disruption severity (i.e., crash on shoulder, crash blocking one lane, crash blocking all but one lane, construction work zone, and rush hour traffic) affect drivers' decisions to divert.

4.1. Subgroup A

The first step of the data analysis was a descriptive frequency analysis. Simple frequency results illustrate general trends in survey data, including how the survey subjects responded to the questions. The majority of the drivers indicated that travel time was a key factor in their decision to seek an alternate travel route when confronted with an incident that adversely impacted their travel. Over three quarters of the survey respondents (76.2 percent) indicated that they either "strongly" or "somewhat" agreed that travel time was important. While 16.2 percent neither agreed or disagreed, only 7.8 percent either "somewhat" or "strongly" disagreed that it was important to them.

In terms of the distance required to travel the results were somewhat the opposite. Nearly 60 percent of the surveyed drivers "somewhat" or "strongly" disagree that the length of a diversionary route to avoid delay was important. And while 18.5 percent of the drivers indicated no influence, only 22.6 "somewhat" or "strongly" agreed that travel distance was a crucial factor in their decision-making process.

Survey results also showed that the safety (in terms of crime or other perceived threats to personal safety) of the surrounding area along an alternate route were also important to the large majority of drivers. Once again nearly three quarters (73.3 percent) of surveyed drivers “strongly” or “somewhat” agreed that possible threats to their personal safety were important considerations in deciding whether to divert to an alternate route. While 18.0 percent neither agreed or disagreed that it was important, only 7.8 percent either “somewhat” or “strongly” disagreed that it was important to them.

To further investigate these results, a multivariate analysis of variance (MANOVA) was conducted to evaluate the hypothesis that there would be one or more mean main effect differences between gender, age, among the potentially influential factors of diversionary behavior. The results of the MANOVA analysis for the influential factors of diversionary driver behavior are shown in Table 1. A statistically significant MANOVA effect was observed for both main effects, gender and age, and an interaction effect between gender and age. This indicated that there was a statistically significant difference between the demographic variables and what influenced diversionary behavior.

Table 1. Subgroup A MANOVA Summary of Results

Source	***Hotelling's Trace Value***	***Exact F***	***d.f.***	***Error d.f.***	***Effect Size***	***Significance***
Gender	0.013	2.604	5	999	0.013	**0.024**
Age	0.014	2.745	5	999	0.014	**0.018**
Gender × Age	0.011	2.230	5	999	0.011	**0.049**

The results of MANOVA testing showed that gender had a Hotelling’s Trace value of 0.013, an F-value of 2.604 and a significance level of $p = 0.024$. Combined, these statistics suggest that there was a statistically significant difference in the influences of diversion between males and females. The multivariate effect size was estimated at 0.013, implying that 1.3 percent

of the variance in the dependent variables were accounted for by gender. Similarly, MANOVA testing of age showed a Hotelling's Trace value of 0.014, an F-value of 2.745, and a significance level of 0.018. Once again suggesting a statistically significant difference in the influences of diversion between younger and older individuals. Also, the multivariate effect size was estimated at 0.014, implying that 1.4 percent of the variance in the dependent variables were accounted for by age.

While these statistics all reveal significant differences between the various driver categories, the slight differences in the multivariate effect of size also suggests that none of them were practically significant. In lay terms, this meant that the various groups would be expected to behave similarly to motivational factors like travel time, distance, time of day, familiarity, and safety perceptions as well as how guidance would be provided to them.

Next, the descriptive means of the effects of gender and age on the influential factors of diversionary driver behavior were assessed across the test variables. The results of this testing are summarized in Table 2. As the survey was analyzed on a one-to-five scale, one implied strong disagreement to a question and five implied strong agreement. Overall, the mean of all questions related to influential factors in the survey was 3.37. The following sections briefly highlight and describe the descriptive statistical mean results for the factors.

Table 2. Subgroup A Descriptive Means Summary of Results

Gender	***Age***	**Travel Time**	**Route Length**	**Safety of Surroundings**	**Time of Day**	**Familiarity with Area**	**Average of All Responses**
Male	**18-34**	**3.76**	2.59	**3.73**	**3.76**	2.64	3.30
	35+	4.08	2.51	3.96	3.93	2.66	3.43
	Total	3.90	2.56	3.83	3.83	2.65	3.35
Female	**18-34**	4.00	2.50	4.00	3.98	**2.45**	3.39
	35+	3.96	**2.39**	4.00	4.04	2.57	3.39
	Total	3.98	2.45	4.00	4.01	2.51	3.39
Total	**18-34**	3.96	2.55	3.84	3.85	2.56	3.35
	35+	4.02	2.45	3.98	3.98	2.62	3.41
	Total	3.94	**2.51**	3.90	3.91	**2.59**	3.37

4.1.1. Travel Time

Descriptive analyses of travel time showed an average of 3.94 across all groups. Interestingly, the mean response of younger male drivers was nearly five percent lower than the overall mean of other groups, implying that younger males may be the least likely to be influenced by travel time compared to older males and all females. Conversely, the group with the largest mean ($\bar{x}$ = 4.08) were older males. This suggests that older males may be more likely to be motivated by time savings when selecting an alternate travel path when compared to all other drivers.

The relationship between gender and travel time revealed the females had a higher mean (3.98) than males (3.90). This could imply that females are more likely to be motivated by travel time when compared to males. Similarly, the relationship between age and travel time shows that younger participants had a lower mean ($\bar{x}$ = 3.96) than older participants ($\bar{x}$ = 4.02), potentially suggesting that younger drivers are less likely to divert based on travel time compared to older individuals.

4.1.2. Route Length

The average survey-wide response value for the route length was 2.51. At 25.5 percent below the overall mean of the sample this influential variable had the lowest mean of the five examined in the study. Among the surveyed drivers the older female group showed the lowest mean response value ($\bar{x}$ = 2.39) of the subgroup potentially implying that they were less likely to be influenced by route length when compared the other driver groups. On the other hand, younger male drivers had the largest mean value ($\bar{x}$ = 2.59) suggesting they could be more influenced by longer or shorter driving distances compared to other drivers.

The relationship between gender and route length showed that males had a higher mean ($\bar{x}$ = 2.56) than females ($\bar{x}$ = 2.45) potentially implying that men are more influenced by route length compared to women. The relationship between age and travel time also shows that older driver groups had a lower mean ($\bar{x}$ = 2.45) compared to younger drivers ($\bar{x}$ = 2.55). Once again, this may suggest that older drivers are less motivated by route length compared to younger drivers.

4.1.3. Safety of Surroundings

The average response value for the safety of the surroundings on an alternative route was 3.90. This was 15.7 percent higher than the overall mean of the sample and the third highest mean of the five influential factors. Analysis of the category means showed that younger male drivers had the lowest average ($\bar{x}$ = 3.73) among the age and gender categories, potentially implying that younger males are less concerned with the safety of their surroundings compared to other driver groups. In contrast, females and the highest mean response ($\bar{x}$ = 4.00) potentially suggest that female drivers, in general, may be more likely to select alternate routes compared to male drivers. A similar difference was evident between younger and older drivers. Young drivers

had a lower mean response value ($\bar{x}$ = 3.84) than older drivers ($\bar{x}$ = 3.98) potentially suggesting that the routes taken by younger drivers are less affected by the perceived issues of safety compared to their older counterparts.

4.1.4. Time of Day

The mean value of the time-of-day factor among all drivers was 3.91, 16.0 percent higher than the overall mean of the sample. This was the second highest mean of the five factors examined suggesting its importance to diversion choice. Among the various categories younger male drivers had the lowest average response ($\bar{x}$ = 3.76) suggesting that they would be less influenced by the time of day compared to other drivers. Older females had the highest mean response value ($\bar{x}$ = 4.04) suggesting that they were more influenced by clock time than any other driver group. More specifically, the higher mean ($\bar{x}$ = 4.01) of all female drivers compared to males ($\bar{x}$ = 3.83) may imply that they are more sensitive to time than men. Similarly, the difference in the response means of older drivers ($\bar{x}$ = 3.98) compared to ($\bar{x}$ = 3.85) for younger drivers suggests that they are more sensitive to time of day than younger drivers when making route diversion decisions.

4.1.5. Familiarity with Area

The final factor analyzed in Subgroup A was the effect of familiarity with potential diversionary routes and areas. The mean value for this variable was 2.59 at 23.1 percent less than the overall mean of the sample; it also had the second lowest mean of any of the five factors in the survey. Mean response values of younger female drivers ($\bar{x}$ = 2.45) suggested that they were the least likely to be influenced by familiarity compared to all other driver categories. By contrast older males had the highest mean ($\bar{x}$ = 2.66) suggesting that they were the most likely to be influenced by their familiarity with an area when compared to any other group.

The relationship between gender and familiarity showed the men had a higher mean response value ($\bar{x}$ = 2.65) than women ($\bar{x}$ = 2.51) potentially implying that they would be more likely influenced by their familiarity with the area when compared to women. A similar relationship was also evident between younger and older drivers. Here, older drivers had a higher mean response ($\bar{x}$ = 2.62) than younger drivers (2.56) suggesting that they were more likely to be influenced by their familiarity with an alternate route and its surrounding area than younger drivers.

4.2. Subgroup B

The first step of the data analysis was a descriptive frequency analysis. Simple frequency results illustrate general trends in survey data, including how participants answered survey questions. The majority of drivers indicated that they would divert from their current route when confronted with a crash on the shoulder of the road. Nearly three quarter of the survey respondents (74.3 percent) indicated that they either “strongly” or “somewhat” agreed that they would use an alternate route when in this situation. While 16.6 percent neither agreed nor disagreed, only 9.2 percent “somewhat” or “strongly” disagreed that they would utilize an alternate route when they are confronted with a crash on the shoulder of the road.

When respondents were questioned on whether they would divert when encountering a crash that blocked all but one lane of the road, nearly three quarters of the surveyed drivers (73.4 percent) “somewhat” or “strongly” agreed that they would utilize an alternate route. While 17.3 percent of the drivers indicated no influence, only 9.4 percent “somewhat” or “strongly” disagreed that they would divert when confronted with a crash that blocked all but one lane of the road.

Survey results also showed that construction work zones along a route were important to the large majority of the surveyed drivers. Once again, nearly three quarters (74.4 percent) of respondents indicated that they “somewhat” or “strongly” agreed that they would be inclined to use an alternate route when encountering a construction work zone. While 15.8 percent neither agreed nor disagreed, only 9.8 percent of surveyed drivers either “somewhat” or “strongly” disagreed that they would divert when confronted with a construction work zone.

To further investigate these results, a multivariate analysis of variance (MANOVA) was conducted to test the hypothesis that there would be one or more mean differences between gender, age, and education level among the potentially influential factors of diversionary behavior. The results of the MANOVA analysis for the disruption severity to cause diversionary driver behavior are shown in Table 3. A statistically significant MANOVA effect was observed for gender, age, and education level. The interactions between gender and age, gender and education, age and education; and gender, age, and education had no statistical significance. This indicated that there was a statistically significant difference between the demographic variables and what influenced diversionary behavior individually, but not in the interactions between the variables.

The results of MANOVA testing showed that gender had a Hotelling’s Trace value of 0.015, an F-value of 2.991 and a significance level of 0.011. Combined, these statistics suggest that there was a statistically significant difference in the influences of diversion between males and females. The multivariate effect size was estimated at 0.015, implying that 1.5 percent of the variance in the dependent variables were accounted for by gender. Similarly, MANOVA testing of age showed a Hotelling’s Trace value of 0.011, an F-value of 2.128, and a significance level

of 0.060. Once again suggesting a statistically significant difference, per a 90 percent confidence level, in the influences of diversion between younger and older individuals.

Table 3. Subgroup B MANOVA Summary of Results

Source	***Hotelling's Trace Value***	***Exact F***	***d.f.***	***Error d.f.***	***Effect Size***	***Significance***
Gender	0.015	2.991	5	975	0.015	**0.011**
Age	0.011	2.128	5	975	0.011	**0.060**
Education	0.021	2.014	10	1948	0.021	**0.029**
Gender x Age	0.002	0.392	5	975	0.002	0.854
Gender x Education	0.012	1.215	10	1948	0.012	0.276
Age x Education	0.016	1.534	10	1948	0.016	0.121
Gender x Age x Education	0.005	0.536	10	1948	0.005	0.866

Additionally, the multivariate effect size was estimated at 0.011, implying that 1.1 percent of the variance in the dependent variables were accounted for by age. Lastly, MANOVA testing of education level showed a Hotelling's Trace value of 0.021, an F-value of 2.014, and a significance level of 0.029. Once again suggesting a statistically significant difference in the influences of diversion between varying levels of education. Also, the multivariate effect size was estimated at 0.021, implying that 2.1 percent of the variance in the dependent variables were accounted for by education level.

While these statistics reveal significant differences between the various driver categories, the small differences in the multivariate effect of size also suggests that none of them were practically significant. In lay terms, this meant that the various groups would be expected to behave similarly despite the severity of disruptions like a crash on the shoulder, a crash blocking all but one lane of the road, a construction work zone, and routine rush hour traffic.

Next, the descriptive means of the effects of gender, age, and education level on the diversionary driver behavior were assessed across the test variables. The results of this testing are summarized in Table 4. As subjects were surveyed on a one-to-five scale, a one implied strong disagreement to a question and five implied strong agreement. Overall, the mean of all questions related to the diverting due to various severities of a disruption in the survey was 3.38. The following sections briefly highlight and describe the descriptive statistical mean results for the factors.

Table 4. Subgroup B Descriptive Means Summary of Results

Gender	*Age*	*Education*	**Crash on Shoulder**	**Crash Blocking One Lane**	**Crash Blocking All But One Lane**	**Construction Work Zone**	**Rush Hour Traffic**	**Average of All Responses**
Male	**18-34**	**Some college & 2-year**	3.24	2.67	3.27	3.18	2.94	3.06
		4-year	3.81	2.64	3.77	3.89	2.65	3.35
		Professional & Doc.	3.73	2.67	3.83	3.98	2.65	3.37
		Total	3.74	2.65	3.73	3.83	2.68	3.33
	35+	**Some college & 2-year**	3.57	2.83	3.91	3.78	2.87	3.39
		4-year	3.94	2.61	3.85	3.89	2.60	3.38
		Professional & Doc.	4.05	2.51	4.00	4.00	2.56	3.42
		Total	3.92	2.62	3.88	3.90	2.62	3.39
	Total	**Some college & 2-year**	3.38	2.73	3.54	3.43	2.91	3.20
		4-year	3.86	2.63	3.80	3.89	2.63	3.36
		Professional & Doc.	3.86	2.60	3.90	3.99	2.61	3.39
		Total	3.81	2.64	3.80	3.86	2.66	3.35
Female	**18-34**	**Some college & 2-year**	3.83	3.25	3.58	3.50	2.83	3.40
		4-year	4.02	2.71	4.00	3.98	2.56	3.45
		Professional & Doc.	3.84	2.88	3.78	3.94	2.88	3.46
		Total	3.97	2.77	3.93	3.95	2.64	3.45

(table cont'd.)

Gender	*Age*	*Education*	Crash on Shoulder	Crash Blocking One Lane	Crash Blocking All But One Lane	Construction Work Zone	Rush Hour Traffic	Average of All Responses
	35+	Some college & 2-year	4.00	3.10	4.35	3.65	2.90	3.60
		4-year	3.89	2.59	3.86	3.96	2.64	3.39
		Professional & Doc.	4.04	3.06	3.96	3.96	2.87	3.58
		Total	3.93	2.74	3.92	3.93	2.71	3.45
	Total	Some college & 2-year	3.94	3.16	4.06	3.59	2.88	3.53
		4-year	3.96	2.65	3.93	3.97	2.60	3.42
		Professional & Doc.	3.94	2.97	3.87	3.95	2.88	3.52
		Total	3.95	2.76	3.93	3.94	2.68	3.45
Total	18-34	Some college & 2-year	3.40	2.82	3.36	3.27	2.91	3.15
		4-year	3.90	2.67	3.87	3.93	2.61	3.40
		Professional & Doc.	3.78	2.76	3.81	3.96	2.75	3.41
		Total	3.83	2.70	3.81	3.88	2.67	3.38
	35+	Some college & 2-year	3.77	2.95	4.12	3.72	2.88	3.49
		4-year	3.91	2.60	3.85	3.93	2.62	3.38
		Professional & Doc.	4.04	2.80	3.98	3.98	2.72	3.50
		Total	3.93	2.68	3.90	3.92	2.67	3.42
	Total	Some college & 2-year	3.58	2.89	3.73	3.49	2.90	3.32
		4-year	3.91	2.64	3.86	3.93	2.62	3.39
		Professional & Doc.	3.90	2.78	3.88	3.97	2.74	3.45
		Total	3.88	2.69	3.85	3.90	2.67	3.40

4.2.1. Crash on Shoulder

Descriptive analysis of crashes on the shoulder of the road showed an average of 3.88 across all groups. Interestingly, the mean response of younger males with either some college education or a 2-year degree was 16.5 percent lower than the overall mean of other groups, implying that younger males with a lower education level may be the least likely to utilize an

alternate route when encountering a crash on the shoulder of the road compared to older males and all females of higher education levels. Conversely, the group with the largest mean ($\bar{x}$ = 4.05) were older males with a professional or doctoral degree. This suggests that older males with a higher education may be more likely to divert when confronted with a crash on the shoulder of the road when compared to all other drivers.

The relationship between gender and diverting when encountering a crash on the shoulder of the road revealed that females had a higher mean ($\bar{x}$ = 3.95) than males ($\bar{x}$ = 3.81). This could imply that females are more likely to use an alternate route when confronted with a crash on the shoulder of the road when compared to males. Similarly, the relationship between age and diverting in this scenario shows that younger participants had a lower mean ($\bar{x}$ = 3.83) than older participants ($\bar{x}$ = 3.93), potentially suggesting that younger drivers are less likely to divert when they encounter a crash on the shoulder of the road compared to older individuals. Because the independent variable, education level, is divided into three groups, a Duncan post hoc test was completed to analyze any differences in the means. The relationship between education level and using an alternate route when confronted with a crash on the shoulder of the road is summarized in Table 5. Drivers with either some college education or a 2-year degree had a lower mean ($\bar{x}$ = 3.58) than all other education levels ($\bar{x}$ = 3.91). This implies that individuals with a lower education are less likely to divert due to a crash on the shoulder of the road when compared to individuals with a higher education level.

Table 5. Duncan Post Hoc Test for Crash on Shoulder

Education Level	**Subgroup 1**	**Subgroup 2**
Some college & 2-year	3.58	
Professional & Doc.		3.90
4-year		3.91
Significance	1.000	0.952

4.2.2. Crash Blocking One Lane

The average survey-wide response value for crashes blocking one lane of the road was 2.69. At 20.9 percent less than the overall mean of the sample, this level of disruption severity was the second lowest of the five situations examined in the study. Among the surveyed drivers, older males with either a professional or doctoral degree showed the lowest mean response value ($\bar{x}$ = 2.51) of the subgroup potentially implying that they were less likely to divert when encountering a crash that blocked one lane of the road when compared to other driver groups. On the other hand, younger females with either some college education or a 2-year degree had the largest mean ($\bar{x}$ = 3.25) suggesting they could be more likely to utilize an alternate route when confronted with a crash that blocked one lane of the road compared to other drivers.

The relationship between gender and diverting when encountering a crash that blocks one lane of the road showed that females had a higher mean ($\bar{x}$ = 2.76) than females ($\bar{x}$ = 2.64) potentially implying that women are more likely to use an alternate route to avoid a crash that blocks one lane of a road compared to men. The relationship between age and diverting in this disruption scenario shows that older driver groups had a lower mean ($\bar{x}$ = 2.68) compared to younger drivers ($\bar{x}$ = 2.70). Once again, this may suggest that older drivers are less inclined that divert when they encounter a crash that blocks one lane of the road compared to younger drivers.

4.2.3. Crash Blocking All But One Lane

The average response value for a crash that blocks all but one lane of the road was 3.85. This was 13.2 percent higher than the overall mean of the sample and the third highest mean of the five disruption severities examined in the study. Analysis of the category means showed that younger male drivers with either some college education or a 2-year degree had the lowest average ($\bar{x}$ = 3.27) among the age, gender, and education level categories, potentially implying

that they are less likely to divert when confronted with a crash that blocks all but one lane of the road compared to other driver groups. In contrast, females had the highest mean response ($\bar{x}$ = 3.92) which potentially suggests that female drivers, in general, may be more likely to use an alternate route when they encounter a crash that blocks all but one lane of the road compared to male drivers. A similar difference was evident between younger and older drivers. Young drivers had a lower mean response value ($\bar{x}$ = 3.81) than older drivers ($\bar{x}$ = 3.90) potentially suggesting that younger drivers are less likely to divert from a crash that blocks all but one lane of the road compared to their older counterparts.

4.2.4. Construction Work Zone

The mean value of the effect of a construction work zone on diversion among all drivers was 3.90. This was 14.7 percent higher than the overall average of the sample and was the highest mean of the five scenarios examined suggesting its importance on diversionary behavior. Amount the various categories, younger male drivers with either some college education or a 2-year degree had the lowest average ($\bar{x}$ = 3.18) suggesting that they would be less likely to use an alternate route when approaching a construction work zone compared to other drivers. Similar to a crash on the shoulder of the road, older males with a professional or doctoral degree had the highest mean response value ($\bar{x}$ = 4.00) suggesting that they were more likely to avoid a construction work zone through diversion than any other driver group.

More specifically, the higher mean ($\bar{x}$ = 3.94) of all female drivers compared to males ($\bar{x}$ = 3.86) may imply that they are more sensitive to construction work zones than men. Similarly, the difference in the response means of older drivers ($\bar{x}$ = 3.92) compared to ($\bar{x}$ = 3.88) for younger drivers suggests that they are more sensitive to construction work zones than younger drivers when making route diversion decisions. Similar to a crash on the shoulder of the road, a

Duncan post hoc test was completed to analyze any differences in the means. The relationship between education level and using an alternate route when confronted with a construction work zone is summarized in Table 6. Drivers with either some college education or a 2-year degree had a lower mean ($\bar{x}$ = 3.49) than all other education levels ($\bar{x}$ = 3.95). This could imply that individuals with a lower education are less likely to divert due to a construction work zone when compared to individuals with a higher education level.

Table 6. Duncan Post Hoc Test for Construction Work Zone

Education Level	**Subgroup 1**	**Subgroup 2**
Some college & 2-year	3.49	
4-year		3.93
Professional & Doc.		3.97
Significance	1.000	0.687

4.2.5. Rush Hour Traffic

The final scenario analyzed in the Subgroup B was the effect of rush hour traffic on potential diversionary behaviors. The mean value for this scenario was 2.67 at 21.5 percent less than the overall mean of the sample; it also had the lowest mean of any of the five scenarios in the survey. Mean response values of older male drivers with either a professional or doctoral degree ($\bar{x}$ = 2.56) suggested that they were the least likely to divert from rush hour traffic compared to all other driver categories. By contrast, younger male drivers with either some college education or a 2-year degree had the highest mean ($\bar{x}$ = 2.94) suggesting that they were the more likely to use an alternate route to avoid rush hour traffic when compared to any other group.

The relationship between gender and diverting from rush hour traffic showed that women had a higher mean ($\bar{x}$ = 2.68) than men ($\bar{x}$ = 2.66) potentially implying that they would be more likely to divert to avoid rush hour traffic compared to men. A similar relationship was evident

between drivers of various education levels. A Duncan post hoc test was completed to analyze any differences in the means. The relationship between education level and using an alternate route when confronted with rush hour traffic is summarized in Table 7. Surveyed drivers with a 4-year degree had a lower mean ($\bar{x}$ = 2.62) than those with either some college education or a 2-year degree ($\bar{x}$ = 2.90). This could imply that individuals with a 4-year degree are less likely to divert due to rush hour traffic when compared to individuals with a lower education level.

Table 7. Duncan Post Hoc Test for Rush Hour Traffic

Education Level	**Subgroup 1**	**Subgroup 2**
4-year	2.62	
Professional & Doc.	2.74	2.74
Some college & 2-year		2.90
Significance	0.354	0.233

4.3. Subgroup C

The first step of the data analysis was a descriptive frequency analysis. Simple frequency results illustrate general trends in survey data, including how the survey subjects responded to the questions. The majority of the drivers indicated that travel time was a key factor in their decision to seek an alternate travel route when confronted with an incident that adversely impacted their travel. Over three quarters of the survey respondents (82.2 percent) indicated that they either “strongly” or “somewhat” agreed that travel time was important. While 9.8 percent neither agreed nor disagreed, only 8.0 percent either “somewhat” or “strongly” disagreed that it was important to them.

In terms of the distance required to travel the results were somewhat the opposite. Nearly 51.5 percent of the surveyed drivers “somewhat” or “strongly” disagree that the length of a diversionary route to avoid delay was important. And while 17.5 percent of the drivers indicated

no influence, only 32.0 percent “somewhat” or “strongly” agreed that travel distance was an important factor in their decision-making process.

Survey results also showed that the safety (in terms of crime or other perceived threats to personal safety) of the surrounding area along an alternate route were also important to the large majority of drivers. Once again over three quarters (77.5 percent) of surveyed drivers “strongly” or “somewhat” agreed that possible threats to their personal safety were important considerations in deciding whether to divert to an alternate route. While 16.7 percent neither agreed or disagreed that it was important, only 9.8 percent either “somewhat” or “strongly” disagreed that it was important to them.

Subgroup C studied how the influential factors of diversion are affected by area type. Using ArcGIS Pro™, the geographic location provided by Qualtrics™ via latitudes and longitudes was cross compared with the participants’ responses to the question regarding geographic region. The result of the cross comparison completed to ensure the most accurate survey sample is shown in Figure 1. The figure displays the six geographic regions, as well as the distinction of area type for each datapoint.

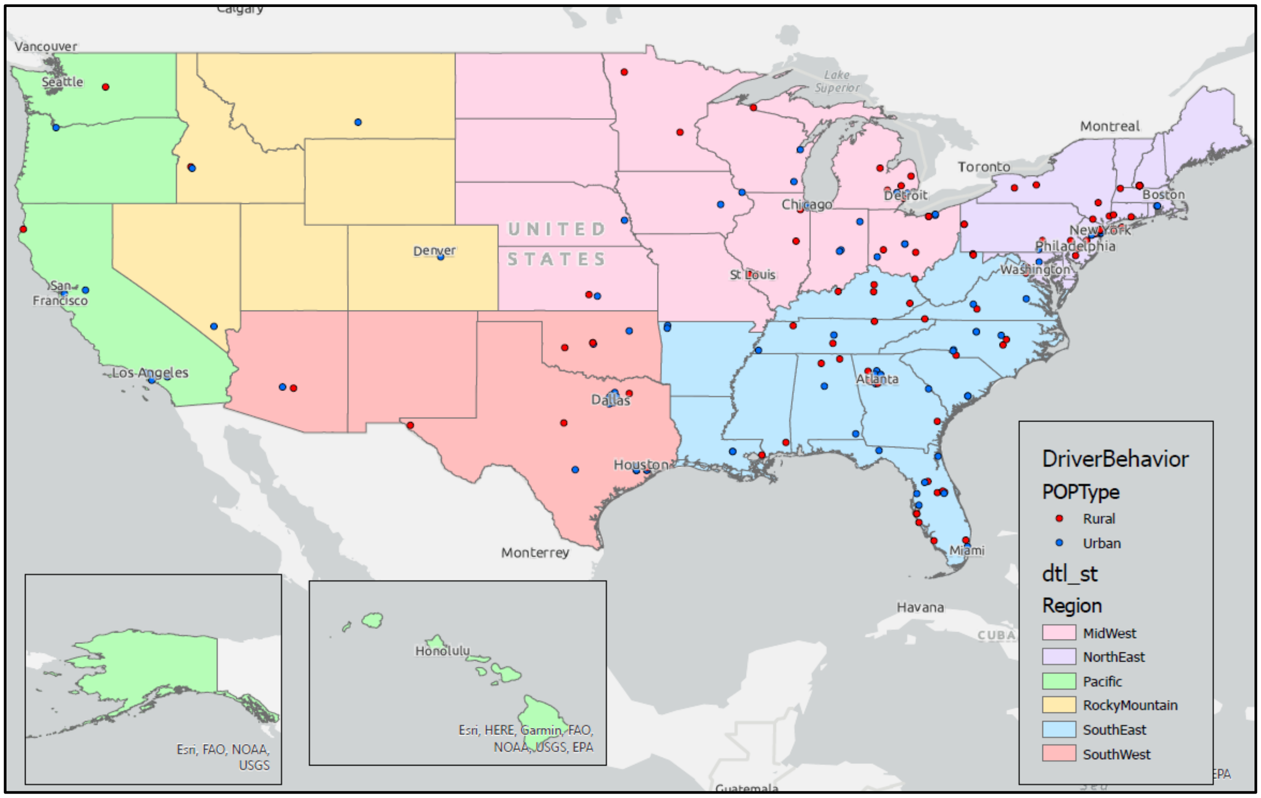

Figure 1. Subgroup C Survey Responses Across the United States

To further investigate the subgroup, a univariate analysis of variance (ANOVA) was conducted to test the hypothesis that there would be one or more mean differences within the area type, among the potentially influential factors of diversionary behavior. The results of the ANOVA analysis for the influential factors of diversionary driver behavior are shown in Table 8. A statistically significant ANOVA effect was observed for travel time and route length. This indicated that there was a statistically significant difference between the area type and what influenced diversionary behavior.

Table 8. Subgroup C ANOVA Summary of Results

Influential Factor	***df***	***Mean Square***	***Exact F***	***Significance***
Travel Time	1	4.487	5.964	**0.015**
Route Length	1	6.953	4.412	**0.037**
Safety of Surroundings	1	0.023	0.031	0.86
Time of Day	1	1.996	2.16	0.143
Familiarity with Area	1	0.149	0.093	0.731

The results of ANOVA testing showed that travel time had a mean square value of 4.487, an F-value of 5.964, and a significance level of 0.015. Combined, these statistics suggest that there was a statistically significant difference in the influence of travel time on diversion between urbanized and non-urbanized areas. Similarly, ANOVA testing of the length of an alternate route showed a mean square value of 6.953, an F-value of 4.412, and a significance level of 0.037. Together, this suggests that there was a statistically significant difference in the influence of route length on diversion between urbanized and non-urbanized areas. The results of the ANOVA test also indicated that the safety of the surroundings, time of day, and familiarity with the area displayed no statistically significant differences between urbanized and non-urbanized areas.

Next, the descriptive means of the effect area type on the influential factors of diversionary driver behavior were assessed across the test variables. The results of this are summarized in Table 9. As the survey was analyzed on a one-to-five scale, one implied strong disagreement to a question and five implied strong agreement. Overall, the mean of all questions related to influential factors in the survey was 3.49. The following sections briefly highlight and describe the descriptive statistical mean results for the factors.

Table 9. Subgroup C Descriptive Means Summary of Results

Influential Factor	**Urban**	**Non-Urban**	**Total**
Travel Time	3.91	4.17	4.02
Route Length	2.65	2.97	2.79
Safety of Surroundings	3.97	3.95	3.96
Time of Day	3.77	3.94	3.84
Familiarity with Area	2.83	2.87	2.85
Average of All Responses	3.43	3.58	3.49

A descriptive analysis of how area type affected what influenced drivers to divert was conducted to observe if urbanized areas acted similarly to non-urbanized areas in disruptive

events. The analysis displayed that travel time, the safety of the surroundings, and the drivers' familiarity with the area were the most influential factors in diversion. On the other hand, factors such as the length of the alternate route or the time of day were proven to be less important to drivers when diverting from a traffic disruption.

The descriptive means portray that urbanized areas had a higher mean ($\bar{x}$ = 3.97) for the safety of surroundings factor than non-urbanized areas. This suggests that drivers in urbanized areas are more influenced by the safety of their surroundings, when compared to drivers in non-urbanized areas. Conversely, the descriptive analysis show that non-urbanized areas had a higher mean for the remaining influential factors that were examined. Non-urbanized areas had a higher mean ($\bar{x}$ = 4.17) for travel time than urbanized areas. This potentially implies that drivers in non-urbanized areas are more influenced by travel time, when compared to drivers in urbanized areas. Similarly, the descriptive means display that non-urbanized areas had a higher mean ($\bar{x}$ = 2.79) for route length when compared to urbanized areas. This potentially implies that drivers in non-urbanized areas are more influenced by route length, when compared to drivers in urbanized areas. The descriptive analysis also illustrated that non-urbanized areas had a higher mean ($\bar{x}$ = 3.94) for the time of day when compared to urbanized areas. This potentially implies that drivers in non-urbanized areas are more influenced by the time of day than drivers in urbanized areas. Lastly, non-urbanized areas had a higher mean ($\bar{x}$ = 2.87) for the familiarity with the area when compared to urbanized areas. This potentially implies that drivers in non-urbanized areas are more influenced by their familiarity with the area, when compared to drivers in urbanized areas.

4.4. Subgroup D

Subgroup D examined how the influential factors of diversion are affected by area type and education level. To further analyze the subgroup, a multivariate analysis of variance

(MANOVA) was conducted to test the hypothesis that there would be one or more mean differences between area type and education level, among the potentially influential factors of diversionary behavior. The results of the MANOVA analysis for the influential factors of diversionary driver behavior are shown in Table 10. A statistically significant MANOVA effect was observed for area type and the interaction between area type and education level. This indicated that there was a statistically significant difference between the demographic variables and what influenced diversionary behavior.

Table 10. Subgroup D MANOVA Summary of Results

Source	*Hotelling's Trace Value*	*Exact F*	*df*	*Error df*	*Effect Size*	*Significance*
Area Type	0.037	1.882	5	254	0.037	**0.098**
Education	0.055	1.375	10	506	0.055	0.186
Area Type x Education	0.101	2.564	10	506	0.101	**0.005**

The results of MANOVA testing showed that area type had a Hotelling's Trace value of 0.037, an F-value of 1.882 and a significance level of 0.098. Combined, these statistics suggest that there was a statistically significant difference in the influences of diversion between urbanized and non-urbanized areas, per a 90 percent confidence level. The multivariate effect size was estimated at 0.037, implying that 3.7 percent of the variance in the dependent variables were accounted for by area type. MANOVA testing of education showed a Hotelling's Trace value of 0.055, an F-value of 1.375, and a significance level of 0.186. This suggests that there was no statistically significant difference in the influences of diversion between varying education levels of drivers. Also, the multivariate effect size was estimated at 0.055, implying that 5.5 percent of the variance in the dependent variables were accounted for by education level. Additionally, MANOVA testing of the interaction between area type and education level showed a Hotelling's Trace value of 0.101, an F-value of 2.564, and a significance level of 0.005. Once again suggesting a statistically significant difference in the influences of diversion between the

interaction of area type and varying levels of education of drivers. Also, the multivariate effect size was estimated at 0.101, implying that 10.1 percent of the variance in the dependent variables were accounted for by the interaction between the two demographic variables.

While these statistics all reveal significant differences between the various driver categories, the minor differences in the multivariate effect of size also suggests that none of them were practically significant. In lay terms, this means that the various groups would be expected to behave similarly to motivational factors like travel time, distance, time of day, familiarity, and safety perceptions as well as how guidance would be provided to them.

Table 11. Subgroup D Descriptive Means Summary of Results

Area Type	***Education***	**Travel Time**	**Route Length**	**Safety of Surroundings**	**Time of Day**	**Familiarity with Area**	**Average of All Responses**
Urban	**Some college & 2-year**	3.38	2.85	3.92	3.31	3.08	3.31
	4-year	3.93	2.60	3.99	3.72	2.87	3.42
	Professional & Doc.	4.16	2.77	3.94	4.13	2.52	3.70
	Total	3.93	2.65	3.97	3.77	2.82	3.63
Non-Urban	**Some college & 2-year**	4.48	3.48	4.04	3.85	3.63	3.90
	4-year	4.11	2.69	3.90	4.04	2.45	3.44
	Professional & Doc.	3.85	3.08	3.85	3.69	3.08	3.51
	Total	4.17	2.93	3.93	3.95	2.81	3.56
Total	**Some college & 2-year**	4.13	3.28	4.00	3.68	3.45	3.71
	4-year	4.00	2.63	3.96	3.85	2.71	3.43
	Professional & Doc.	4.07	2.86	3.91	4.00	2.68	3.50
	Total	4.03	2.77	3.95	3.85	2.81	3.48

Next, the descriptive means of the effects of area type and education level on the influential factors of diversionary driver behavior were assessed across the test variables. The results of this are summarized in Table 11. As the survey was analyzed on a one-to-five scale,

one implied strong disagreement to a question and five implied strong agreement. Overall, the mean of all questions related to influential factors in the survey was 3.48. The following sections briefly highlight and describe the descriptive statistical mean results for the factors.

4.4.1. Travel Time

Descriptive analysis of travel time showed an average of 4.03 across all groups. Interestingly, the mean response of drivers in urbanized areas with either some college education or a 2-year degree was 16.1 percent lower than the overall mean of other groups, implying that drivers in urbanized areas with a lower education level may be the least likely to be influenced by travel time compared to drivers in non-urbanized areas and any drivers with higher education levels. Conversely, the group with the largest mean ($\bar{x}$ = 4.48) were drivers in non-urbanized areas with either some college education or a 2-year degree. This suggests drivers in non-urbanized areas with a lower education level may be more likely to be motivated by time savings when selecting an alternate travel path when compared to all other drivers.

The relationship between area type and travel time revealed that drivers in non-urbanized areas had a higher mean ($\bar{x}$ = 4.17) than drivers in urbanized areas ($\bar{x}$ = 3.93). This could imply that drivers in non-urbanized areas are more likely to be motivated by travel time when compared to drivers in urbanized areas.

4.4.2. Rout*e Length*

The average survey-wide response value for the route length was 2.77. At 20.4 percent below the overall mean of the sample this influential variable had the lowest mean of the five examined in the study. Among the surveyed participants, drivers in urbanized areas with a 4-year degree showed the lowest mean response value ($\bar{x}$ = 2.60) of the subgroup potentially implying that they were less likely to be influenced by route length when compared the other driver

groups. On the other hand, drivers in non-urbanized areas with either some college education or a 2-year degree had the largest mean value ($\bar{x}$ = 3.48) suggesting they could be more influenced by longer or shorter driving distances compared to other drivers.

The relationship between area type and route length showed that drivers in non-urbanized areas had a higher mean ($\bar{x}$ = 2.93) than drivers in urbanized areas ($\bar{x}$ = 2.65) potentially implying that drivers in non-urbanized areas are more influenced by route length compared to drivers in urbanized areas. Because the independent variable, education level, is divided into three groups, a Duncan post hoc test was completed to analyze any differences in the means. The relationship between education level and the influence of the length of an alternate route on diversion is summarized in Table 12. Surveyed drivers with a 4-year degree had a lower mean ($\bar{x}$ = 2.63) than drivers with either some college education or a 2-year degree ($\bar{x}$ = 3.28). This could imply that individuals with a lower education are more likely to be influenced by the length of an alternate route when diverting than to individuals with a higher education level.

Table 12. Duncan Post Hoc Test for Route Length

Education Level	**Subgroup 1**	**Subgroup 2**
4-year	2.63	
Professional & Doc.	2.86	2.86
Some college & 2-year		3.28
Significance	0.321	0.077

4.4.3. Safety of Surroundings

The average response value for the safety of the surroundings on an alternative route was 3.95. This was 13.5 percent higher than the overall mean of the sample and the second highest mean of the five influential factors. Analysis of the category means showed that drivers in non-urbanized areas with either a professional or doctoral degree had the lowest average ($\bar{x}$ = 3.85) among the area type and education categories, potentially implying that drivers in non-urbanized areas with a higher education level are less concerned with the safety of their surroundings

compared to other driver groups. In contrast, the group with the largest mean ($\bar{x}$ = 4.04) were drivers in non-urbanized areas with either some college education or a 2-year degree. This suggests drivers in non-urbanized areas with a lower education level may be more likely to be motivated by the safety of their surroundings when selecting an alternate travel path when compared to all other drivers.

The relationship between area type and the safety of the surroundings revealed that drivers in urbanized areas had a higher mean ($\bar{x}$ = 3.97) than drivers in non-urbanized areas ($\bar{x}$ = 3.93). This could imply that drivers in urbanized areas are more likely to be motivated by the safety of their surroundings when compared to drivers in non-urbanized areas.

4.4.4. Time of Day

The mean value of the time-of-day factor among all drivers was 3.85, 10.6 percent higher than the overall mean of the sample. This was the third highest mean of the five factors examined suggesting its importance to diversion choice. Among the various categories drivers in urbanized areas with either some college education or a 2-year degree had the lowest average response ($\bar{x}$ = 3.31) suggesting that they would be less influenced by the time of day compared to other drivers. Drivers in urbanized areas with either a professional or doctoral degree had the highest mean response value ($\bar{x}$ = 4.13) suggesting that they were more influenced by clock time than any other driver group. More specifically, the higher mean ($\bar{x}$ = 3.95) of all drivers in non-urbanized areas compared to drivers in urbanized areas ($\bar{x}$ = 3.77) may imply that they are more sensitive to time than those in non-urbanized areas.

4.4.5. Familiarity with Area

The final factor analyzed in Subgroup D was the effect of familiarity with potential diversionary routes and areas. The mean value for this variable was 2.81 at 19.3 percent less than

the overall mean of the sample; it also had the second lowest mean of any of the five factors in the survey. Mean response values of drivers in non-urbanized areas with a 4-year degree ($\bar{x}$ = 2.45) suggested that they were the least likely to be influenced by familiarity compared to all other driver categories. By contrast, drivers in non-urbanized areas with either some college education or a 2-year degree had the highest mean ($\bar{x}$ = 3.63) suggesting that they were the most likely to be influenced by their familiarity with an area when compared to any other group.

The relationship between area type and drivers' familiarity with the area showed that drivers in urbanized areas had a higher mean ($\bar{x}$ = 2.82) than drivers in non-urbanized areas ($\bar{x}$ = 2.81) potentially implying that drivers in non-urbanized areas are less influenced by route length compared to drivers in urbanized areas. Because the independent variable, education level, is divided into three groups, a Duncan post hoc test was completed to analyze any differences in the means. The relationship between education level and the influence of the drivers' familiarity with the area on diversion is summarized in Table 13. Surveyed drivers with either a 4-year degree, a professional degree, or a doctoral degree had a lower mean ($\bar{x}$ = 2.70) than drivers with either some college education or a 2-year degree ($\bar{x}$ = 3.45). This could imply that individuals with a lower education are more likely to be influenced by their familiarity with the area when diverting than to individuals with a higher education level.

Table 13. Duncan Post Hoc Test for Familiarity with Area

Education Level	**Subgroup 1**	**Subgroup 2**
Professional & Doc.	2.68	
4-year	2.71	
Some college & 2-year		3.45
Significance	0.918	1.000

4.5. Subgroup E

Subgroup E observed how the influential factors of diversion are affected by area type and gender. To further analyze the subgroup, a multivariate analysis of variance (MANOVA)

was conducted to evaluate the hypothesis that there would be one or more mean differences between area type and gender, among the potentially influential factors of diversionary behavior. The results of the MANOVA analysis for the influential factors of diversionary driver behavior are shown in Table 14. A statistically significant MANOVA effect was observed for area type gender. This indicated that there was a statistically significant difference between the demographic variables and what influenced diversionary behavior.

Table 14. Subgroup E MANOVA Summary of Results

Source	***Hotelling's Trace Value***	***Exact F***	***df***	***Error df***	***Effect Size***	***Significance***
Area Type	0.046	2.447	5	264	0.046	**0.034**
Gender	0.043	2.262	5	264	0.043	**0.049**
Area Type x Gender	0.013	0.699	5	264	0.013	0.624

The results of MANOVA testing showed that area type had a Hotelling's Trace value of 0.046, an F-value of 2.447 and a significance level of 0.034. Combined, these statistics suggest that there was a statistically significant difference in the influences of diversion between urbanized and non-urbanized areas. The multivariate effect size was estimated at 0.046, implying that 4.6 percent of the variance in the dependent variables were accounted for by area type. Similarly, MANOVA testing of gender showed a Hotelling's Trace value of 0.043, an F-value of 2.262, and a significance level of 0.049. Once again suggesting a statistically significant difference, in the influences of diversion between male and female drivers. Also, the multivariate effect size was estimated at 0.043, implying that 4.3 percent of the variance in the dependent variables were accounted for by gender. Lastly, MANOVA testing of the interaction between area type and gender showed a Hotelling's Trace value of 0.013, an F-value of 0.699, and a significance level of 0.624. This suggests that there is no statistically significant difference in the influences of diversion between the interaction of area type and gender of drivers. Also, the

multivariate effect size was estimated at 0.013, implying that 1.3 percent of the variance in the dependent variables were accounted for by the interaction between the two demographic variables.

While these statistics all reveal significant differences between the various driver categories, the minor differences in the multivariate effect of size also suggests that none of them were practically significant. In lay terms, this means that the various groups would be expected to behave similarly to motivational factors like travel time, distance, time of day, familiarity, and safety perceptions as well as how guidance would be provided to them.

Next, the descriptive means of the effects of area type and gender on the influential factors of diversionary driver behavior were assessed across the test variables. The results of this are summarized in Table 15. As the survey was analyzed on a one-to-five scale, one implied strong disagreement to a question and five implied strong agreement. Overall, the mean of all questions related to influential factors in the survey was 3.48. The following sections briefly highlight and describe the descriptive statistical mean results for the factors.

Table 15. Subgroup E Descriptive Means Summary of Results

Area Type	***Gender***	**Travel Time**	**Route Length**	**Safety of Surroundings**	**Time of Day**	**Familiarity with Area**	**Average of All Responses**
Urban	**Male**	3.93	2.69	3.95	3.69	3.02	3.46
	Female	3.86	2.59	3.96	3.85	2.55	3.36
	Total	3.90	2.64	3.95	3.76	2.81	3.41
Non-Urban	**Male**	4.12	3.11	3.83	3.77	3.02	3.57
	Female	4.21	2.77	4.08	4.15	2.68	3.58
	Total	4.16	2.96	3.94	3.94	2.86	3.57
Total	**Male**	3.99	2.87	3.90	3.72	3.02	3.50
	Female	4.01	2.67	4.01	3.98	2.60	3.45
	Total	4.00	2.78	3.95	3.84	2.83	3.48

4.5.1. Travel Time

Descriptive analysis of travel time showed an average of 4.01 across all groups. The mean response of female drivers in urbanized was 3.7 percent lower than the overall mean of other groups, implying that female drivers in urbanized areas may be the least likely to be influenced by travel time compared to male drivers in urbanized areas and all drivers in non-urbanized areas. Conversely, the group with the largest mean ($\bar{x}$ = 4.21) were female drivers in non-urbanized areas. This suggests female drivers in non-urbanized areas may be more likely to be motivated by time savings when selecting an alternate travel path when compared to all other drivers.

The relationship between area type and travel time revealed that drivers in non-urbanized areas had a higher mean ($\bar{x}$ = 4.16) than drivers in urbanized areas ($\bar{x}$ = 3.90). This could imply that drivers in non-urbanized areas are more likely to be motivated by travel time when compared to drivers in urbanized areas. Similarly, the relationship between gender and travel time showed that males had a lower mean ($\bar{x}$ = 3.99) than females ($\bar{x}$ = 4.01), potentially suggesting that male drivers are less likely to divert based on travel time compared to female individuals.

4.5.2. Rout*e Length*

The average survey-wide response value for the route length was 2.78. At 20.1 percent below the overall mean of the sample this influential variable had the lowest mean of the five examined in the study. Among the surveyed participants, female drivers in urbanized areas showed the lowest mean response value ($\bar{x}$ = 2.59) of the subgroup potentially implying that they were less likely to be influenced by route length when compared the other driver groups. On the

other hand, male drivers in non-urbanized areas had the largest mean value ($\bar{x}$ = 3.11) suggesting they could be more influenced by longer or shorter driving distances compared to other drivers.

The relationship between area type and route length showed that drivers in non-urbanized areas had a higher mean ($\bar{x}$ = 2.96) than drivers in urbanized areas ($\bar{x}$ = 2.64) potentially implying that drivers in non-urbanized areas are more influenced by route length compared to drivers in urbanized areas. The relationship between gender and route length showed that males had a higher mean ($\bar{x}$ = 2.87) than females ($\bar{x}$ = 2.67) potentially implying that men are more influenced by route length compared to women.

4.5.3. Safety of Surroundings

The average response value for the safety of the surroundings on an alternative route was 3.95. This was 13.5 percent higher than the overall mean of the sample and the second highest mean of the five influential factors. Analysis of the category means showed that male drivers in non-urbanized areas had the lowest average ($\bar{x}$ = 3.83) among the area type and gender categories, potentially implying that male drivers in non-urbanized areas are less concerned with the safety of their surroundings compared to other driver groups. In contrast, the group with the largest mean ($\bar{x}$ = 4.08) were female drivers in non-urbanized. This suggests female drivers in non-urbanized areas may be more likely to be motivated by the safety of their surroundings when selecting an alternate travel path when compared to all other drivers.

The relationship between area type and the safety of the surroundings showed that drivers in urbanized areas had a higher mean ($\bar{x}$ = 3.95) than drivers in non-urbanized areas ($\bar{x}$ = 3.94) potentially implying that drivers in non-urbanized areas are less influenced by the safety of their surroundings compared to drivers in urbanized areas. A similar difference was evident between male and female drivers. Male drivers had a lower mean response value ($\bar{x}$ = 3.90) than female

drivers ($\bar{x}$ = 4.01) potentially suggesting that the routes taken by male drivers are less affected by the perceived issues of safety compared to their older counterparts.

4.5.4. Time of Day

The mean value of the time-of-day factor among all drivers was 3.84, 10.3 percent higher than the overall mean of the sample. This was the third highest mean of the five factors examined suggesting its importance to diversion choice. Among the various categories male drivers in urbanized areas had the lowest average response ($\bar{x}$ = 3.69) suggesting that they would be less influenced by the time of day compared to other drivers. Female drivers in non-urbanized areas had the highest mean response value ($\bar{x}$ = 4.13) suggesting that they were more influenced by clock time than any other driver group. More specifically, the higher mean ($\bar{x}$ = 3.94) of all drivers in non-urbanized areas compared to drivers in urbanized areas ($\bar{x}$ = 3.76) may imply that they are more sensitive to time than those in non-urbanized areas. Similarly, the relationship between gender and travel time showed that males had a lower mean ($\bar{x}$ = 3.72) than females ($\bar{x}$ = 3.98), potentially suggesting that male drivers are less likely to divert based on the time of day compared to female individuals.

4.5.5. Familiarity with Area

The final factor analyzed in Subgroup E was the effect of familiarity with potential diversionary routes and areas. The mean value for this variable was 2.83 at 18.7 percent less than the overall mean of the sample; it also had the second lowest mean of any of the five factors in the survey. Mean response values of female drivers in urbanized areas ($\bar{x}$ = 2.55) suggested that they were the least likely to be influenced by familiarity compared to all other driver categories. By contrast, male drivers in both urbanized and non-urbanized areas had the highest mean ($\bar{x}$ =

3.02) suggesting that they were the most likely to be influenced by their familiarity with an area when compared to any other group.

The relationship between area type and drivers' familiarity with the area showed that drivers in non-urbanized areas had a higher mean ($\bar{x}$ = 2.86) than drivers in urbanized areas ($\bar{x}$ = 2.81) potentially implying that drivers in non-urbanized areas are more influenced by route length compared to drivers in urbanized areas. A similar difference was evident between male and female drivers. Female drivers had a lower mean response value ($\bar{x}$ = 2.60) than male drivers ($\bar{x}$ = 3.02) potentially suggesting that the routes taken by female drivers are less affected by the familiarity with the area compared to their male counterparts.

CHAPTER 5. SUMMARY AND CONCLUSIONS

Many aspects of transportation rely on the ability to reliably anticipate and forecast the movement of traffic through complex networks under varying conditions. Planning to build new infrastructure and effectively expand existing roads are two examples where the allocation of limited resources needs to be commensurate with future expectations of demand, particularly as it may change in response to disruptions, both expected and unexpected. Over the decades, ever more sophisticated tools and methods have been used to predict future traffic demand at a link-specific level. Today's best network traffic assignment models consistently yield valuable results. However, even the best ones are not perfect and continue to improve. This research represents a step in that improvement by introducing explicit driver choice factors, rather than aggregate shortest time path assumptions, into traffic routing and assignment. It is expected that awareness of these factors could support the integration of driver-specific path diversion in future traffic assignment models and increase the predictive accuracy of future traffic forecasting beyond today's homogeneous shortest time path assumption of driver routing.

The survey of driver motivation and influence revealed trends and ideas that were expected and unexpected. At the aggregate level, there were clear indications that, in many cases, drivers will not seek the shortest time path during routine congestion and even during some disruption scenarios. Additionally, there were elevated levels of consistency between the descriptive numeric means. This was true both within and between the two genders and age groups. As shown in Table 2, the mean of all responses to questions regarding influential factors was 3.37, with a mean of all female responses of 3.39 and a mean of all male responses of 3.39. The mean of all younger male and female responses was 3.35 and mean of all older male and female responses was 3.41. While some similarities between genders were expected, it was

similarly expected that the differences in the way information is first accessed then used by younger drivers compared to their older counterparts would result in clear differences between how the two age groups might be influenced in terms of deciding to divert then choosing a specific route. However, the results suggest that, while there may be differences, they were effectively negligible. More notable differences emerge within and across the age and gender categories for certain influential variables.

Consistent with other similar studies where data is segregated within gender and age groups, statistically significant differences were evident in the importance of the five influential factors when considering the interaction between gender and age. In the study, statistical significance was concluded when observed differences exceeded chance variation. However, statistical significance in this context did not necessarily relate to an increased level of importance of any particular variable. Due to the overall similarity of responses within the sample, it suggests that although there was statistical significance between the variables, individuals were influenced by similar factors to divert from their route.

As anticipated, travel time was the most influential factor on diversionary behavior among all drivers. This is consistent with the findings of previous studies that have consistently shown that when confronted with unavoidable delays on a route, drivers will seek alternatives to minimize travel time. The time of day, along with safety of surroundings, were the next two variables of highest influence to the drivers in the survey. This implied that drivers would be more likely to remain on a congested incident-impacted route if alternate routes pass through areas that they deem as unsafe, particularly at night, or more generally if it is at time when alternate routes may also be congested.

Somewhat unexpectedly, a significant drop in mean was noted in values representing the familiarity with alternate routes and areas and their lengths compared to the other factors. This suggests that drivers would not be as sensitive to their familiarity with the area to which they may be driving in to avoid incident congestion, even if they travel a longer distance to reach their destination as long as it decreased their travel time. This was unexpected because of the increased potential to become lost under such conditions. However, these results may be pointing to the ever-increasing levels of trust in real-time route guidance mobile phone applications which offer routes to minimize travel time and offer turn-by-turn directions.

At the disaggregate level, the data shows differences between men and women of various ages, levels of educational attainment, and area type in which they reside. This was notable in the generally increasing rates of diversion preference as age and levels of educational achievement increased. Differences were most pronounced between moderately educated older women ($\bar{x}$ = 2.94) and correspondingly educated younger men ($\bar{x}$ = 3.06). This may reflect trends identified in prior gender-related studies in which younger women were shown to be more compliant and responsive to communication and social cues than men, particularly younger men. As such, the survey results tend to be consistent with many commonly held perceptions between the sexes and ages of drivers.

Differences in the level of diversion preference were considerably more notable under disruptions and are known to influence drivers to favor changes to alternate routes. Interestingly, the largest differences were between the levels of diversion preference for construction work zones and rush hour traffic. As shown in Table 4, the mean of all of the responses for preferring to divert to avoid rush hour traffic was 2.67, suggesting that the general preference among most drivers was not to divert at all. Further sub-categorizing the results showed that a small range

existed between younger, less-educated males ($\bar{x}$ = 2.94) and similar aged males with a four-year degree ($\bar{x}$ = 2.61). In fact, both men and women in the bachelor category than the higher or lower educational attainment groups. While this is difficult to explain why this was so, it may reflect a potential tendency of some groups to value their value their time more if they are employed on hourly rate of pay or bill their work time at an hourly rate. A further trend evident in the data was that these results were nearly reversed between bachelor-level groups ($\bar{x}$ = 3.93) who showed a higher preference to divert for construction work zone conditions and the lower educational attainment groups ($\bar{x}$ = 3.49) under work zone conditions.

Not surprisingly, trends of route diversion preference tended to increase as the level of road disruptions became more severe. Numeric results associated with crashes that block a single lane of travel ($\bar{x}$ = 2.69) suggested that drivers would prefer not to divert. However, under a one-lane open only situation, the mean jumped to 3.85. While this suggests the importance of travel time to drivers, there could be numerous other facts at play.

Additionally, at the disaggregate level, data suggested that female drivers are more acutely influenced by certain conditions than male drivers. For example, female drivers in non-urbanized areas were more likely to be motivated by time savings when selecting an alternate travel path when compared to all other driver categories and male drivers were less likely to divert based on travel time than females. Somewhat conversely, however, rural area male drivers appeared to be more influenced driving distance, lending support to the notion that diversion is less desirable when in less dense networks with comparatively fewer rerouting options.

A further gender-related difference was recognized due to the increased levels to which female drivers consider safety-related concerns in their routing decisions. Data and analysis showed that male drivers had a lower mean response value than female drivers, suggesting that

the routes taken by men tended to be less influenced by safety perceptions compared to women and older drivers of both sexes. More specifically, results suggested that female drivers in non-urbanized areas were likely to be influenced by the safety of their surroundings when selecting an alternate travel path when compared to all other drivers.

Interestingly and somewhat contradictory results were also evident in terms of the gender differences in route familiarity. Analyses showed that female drivers in urbanized areas were the least likely to be influenced by familiarity to all other driver categories and male drivers in both urbanized and non-urbanized areas were the most likely to be influenced by their familiarity with an area. While it was possible to identify that such differences existed, it was not possible to determine specifically why they were evident. Some have suggested that it could be related to prior gender study that suggests that women are more amendable to taking direction than men and/or even a potentially higher use of navigational devices. The latter of these two ideas is being explored in ongoing parallel research.

Finally, it was hypothesized that the time at which a driver encountered adverse traffic conditions could be a significant influencer of route diversion. Clearly, this was a key consideration with a mean response value of 3.84, 10.3 percent higher than the overall mean of the sample. More specifically, it was thought that the importance of time of day would be more acute in urban areas where morning and evening peak commuter periods would be more disruptive to drivers when they were most sensitive about travel time. Interestingly, however, its influence as a route diversion factor was slightly higher for drivers in non-urbanized, rural areas than for urban drivers. In particular, it was lowest for male drivers and highest for female drivers in non-urbanized areas. One potential explanation for the increased importance in non-urbanized

drivers could be related to some drivers working in more distant urban areas in which time of day could be a more important for long commutes.

Despite the consistencies between the various driver group responses, it was clear that younger male drivers responded differently from other drivers in several categories. For example, younger males showed the lowest mean values in three of the five influence variable categories, despite also showing the same ranked order of variable compared to all other driver groups. These results may also suggest that younger males may, in general, be less likely (or influenced in other ways not explored in this study) to divert from a congested route and in need of particularly crafted messaging and guidance if their compliance to change routes was needed.

Combined, the results of this research indicate that there is considerably wider variation in driver routing decision-making than is currently assumed by most traffic assignment models. And perhaps more important is that driver do not always seek the shortest time path from their origins to their destinations. Such knowledge is important not only from a model improvement standpoint but may also prove useful as more complex analyses for real-time adaptive control systems; connected and autonomous vehicles; transit; and freight movement continue to evolve and come into operation.

APPENDIX A. INSTITUTIONAL REVIEW BOARD APPROVAL

LSU | Office of Research & Economic Development

TO:	Brian Wolshon LSUAM | Col of ENGR | Civil and Environmental Engineering | CC00173
FROM:	Alex Cohen Chairman, Institutional Review Board
DATE:	01-Jul-2022
RE:	IRBAM-22-0685
TITLE:	Influences on Driver Diversionary Behavior in Traffic Disruptions
SUBMISSION TYPE:	Initial Application
Review Type:	Exempt
Risk Factor:	Minimal
Review Date:	01-Jul-2022
Status:	Approved
Approval Date:	01-Jul-2022
Approval Expiration Date:	30-Jun-2025
Exempt Category:	2a
Requesting Waiver of Informed Consent:	Yes
Re-review frequency:	Three Years
Number of subjects approved:	1000
LSU Proposal Number:	
By:	Alex Cohen, Chairman

Continuing approval is CONDITIONAL on:

1. Adherence to the approved protocol, familiarity with, and adherence to the ethical standards of the Belmont Report, and LSU's Assurance of Compliance with DHHS regulations for the protection of human subjects*
2. Prior approval of a change in protocol, including revision of the consent documents or an increase in the number of subjects over that approved.
3. Obtaining renewed approval (or submittal of a termination report), prior to the approval expiration date, upon request by the IRB office (irrespective of when the project actually begins); notification of project termination.
4. Retention of documentation of informed consent and study records for at least 3 years after the study ends.
5. Continuing attention to the physical and psychological well-being and informed consent of the

individual participants, including notification of new information that might affect consent.

6. A prompt report to the IRB of any adverse event affecting a participant potentially arising from the study.
7. Notification of the IRB of a serious compliance failure.
8. **SPECIAL NOTE: When emailing more than one recipient, make sure you use bcc. Approvals will automatically be closed by the IRB on the expiration date unless the PI requests a continuation.**

** All investigators and support staff have access to copies of the Belmont Report, LSU's Assurance with DHHS, DHHS (45 CFR 46) and FDA regulations governing use of human subjects, and other relevant documents in print in this office or on our World Wide Web site at http://www.lsu.edu/research*

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APPENDIX B. SURVEY QUESTIONNAIRE

Influences on Driver Diversionary Behavior in Traffic Disruptions

Introduction

You are invited to participate in a survey on the "Influences of Driver Diversionary Behavior in Traffic Disruptions". The purpose of this survey is to examine and better understand route-diversion behavior by assessing driver decision-making under a range of traffic and guidance conditions. Although there is extensive research related to the way drivers react and are impacted by network flow disruptions, more is needed to better understand how drivers react to disruptions under specific sets of conditions during their trips. What we learn from this survey will help us to better understand the factors that can influence driver diversionary behavior in traffic disruptions as well as what motivates drivers to utilize traffic guidance information during their trips. The survey is intended for all age groups who are currently licensed drivers.

The data collected from this survey will be analyzed and the final results will be composed in a review paper. The survey should take approximately 10-15 minutes of your time, however, for some it could take longer. We hope that you find the experience to be informative and engaging.

Potential Harms, Risks or Discomforts

The collected data from this survey focus on answering research questions specific to the factors that can affect driver diversionary behavior in traffic disruptions and/or the use of real-time traffic guidance information during trips. It is unlikely that there will be any harm or discomfort associated with the survey questions but some further details, such as your age and gender, will be collected. The survey will ask you questions about:

- Travel Habits and Preferences
- Driving Habits
- Opinions Regarding Traffic Guidance Information
- Demographic Characteristics (age and gender)

Should you require further information about the survey to inform your decision to participate, please view the entire contents of the survey below.

Potential Benefits

This study may not benefit you directly yet gaining a better understanding on what influences driver diversionary behavior in traffic disruptions will aid conversations and decisions about how best to provide traffic guidance information on disruptions that will aid all drivers in the United States, while ensuring efficiency in their trip and the transportation network as a whole.

Confidentiality

All collected responses will be treated with the utmost confidentiality and stored securely at Louisiana State University. In our work, no effort will be made to identify respondents to the survey including linking with other data sets that could help in this regard. The data will be kept for a minimum of five years and might be used for further analysis. If you elect to withdraw from the survey, your answers will be permanently removed from the database.

Participation and Withdrawal

Your participation in this study is voluntary. It is your choice to be part of this study or not. If you decide to be part of the study, you can stop (withdraw) from the survey for whatever reason, even after signing the consent form. Your data will be permanently removed from the database.

Information About the Study Results

This study will be completed by May 2023. If you would like to receive a summary of the results personally, please let us know.

Questions About the Study

If you have any questions or need more information about the study itself, the following members of Louisiana State University research team can be contacted:

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IRB Approval #: IRBAM-22-0685
Granted on 01-Jul-2022

Having read the aforementioned information, I understand that by clicking the "yes" button below, I agree to take part in this study under the aforementioned terms and conditions.

☐ Yes, I agree to participate in this survey.

☐ No, I do not agree to participate in this survey.

Section 1: Travel Habits and Preferences

1.1. How often do you visit work?

☐ Never
☐ Annually
☐ Monthly
☐ Weekly
☐ Multiple times a week
☐ Daily

1.2. How often do you visit school?

☐ Never
☐ Annually
☐ Monthly
☐ Weekly
☐ Multiple times a week
☐ Daily

1.3. How often do you visit the gym?

☐ Never
☐ Annually
☐ Monthly
☐ Weekly
☐ Multiple times a week
☐ Daily

1.4. How often do you shop?

☐ Never
☐ Annually
☐ Monthly
☐ Weekly
☐ Multiple times a week
☐ Daily

1.5. How often do you visit recreational areas (e.g., sporting events, restaurants)?

☐ Never
☐ Annually
☐ Monthly
☐ Weekly
☐ Multiple times a week
☐ Daily

1.6. I am willing to complete a trip with heavy rain.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

1.7. I am willing to complete a trip with thick fog.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

1.8. I am <u>unwilling</u> to complete a trip with heavy winds.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

1.9. I am willing to complete a trip with snow or icy road conditions.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

Section 2: Decision-Making Confidence

2.1. I am confident in making diversionary travel decisions.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

2.2. It is difficult for me to make diversionary travel decisions.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

2.3. I often make good diversionary travel decisions.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

Section 3: Driving Habits

3.1. I use an alternate route when I encounter a traffic accident on the shoulder of the road.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.2. I <u>do not</u> use an alternate route when I encounter a traffic accident that blocks one lane of a multi-lane road.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.3. I use an alternate route when I encounter a traffic accident that blocks all but one lane of a multi-lane road.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.4. I use an alternate route when I encounter a construction work zone.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.5. I <u>do not</u> use an alternate route when I encounter rush hour traffic.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.6. I use an alternate route to avoid four-way intersections with traffic signal control.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.7. I use an alternate route to avoid four-way intersections without traffic signal control.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.8. I use an alternate route to avoid roundabouts or traffic circles.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.9. I <u>do not</u> use an alternate route to avoid freeways.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

C.1. For this question, please select somewhat agree.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.10. I use an alternate route to avoid active school zones.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.11. Travel time is an important factor in whether I divert from a route during a trip.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.12. The length of the route is <u>not</u> an important factor in whether I divert from a route during a trip.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.13. The safety of the surroundings is an important factor in whether I divert from a route during a trip.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.14. The time of day is an important factor in whether I divert from a route during a trip.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

3.15. My familiarity with the area is <u>not</u> an important factor in whether I divert from a route during a trip.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

Section 4: Decision-Making Avoidance

4.1. I try to avoid situations that require me to make diversionary travel decisions.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

4.2. I prefer to make decisions related to travel diversion.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

4.3. I <u>do not</u> like to think about issues involving diversionary travel decisions.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

Section 5: Opinions Regarding Traffic Guidance Information

5.1. I do not use real-time traffic guidance information during recurring trips (e.g., work).

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

5.2. I use real-time traffic guidance information during non-recurring trips (e.g., vacation).

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

5.3. I would follow traffic guidance information if I was notified of a traffic disruption ahead of time.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

5.4. I use the radio to access traffic guidance information.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

5.5. I do not use the Department of Transportation to access traffic guidance information.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

5.6. I use digital road signs to access traffic guidance information.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

5.7. I <u>do not</u> use in-vehicle guidance assistance to access traffic guidance information.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

5.8. I use a cellular application to access traffic guidance information.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

5.9. Please rate the following cellular applications in order of usefulness from 1 to 4, where 1 is the most useful and 4 is the least useful.

☐ WAZE
☐ Apple Maps
☐ Google Maps
☐ Map Quest

Section 6: Pressure to Finish

6.1. I feel under pressure to finish travel quickly.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

C.2. For this question, please select strongly disagree.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

6.2. I feel that it is expected of me to arrive at destinations as fast as possible.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

6.3. I feel that I have to hurry up to arrive at my destination.

☐ Strongly disagree
☐ Somewhat disagree
☐ Neither agree nor disagree
☐ Somewhat agree
☐ Strongly agree

Section 7: Demographic Characteristics

7.1. What is your gender?

☐ Male
☐ Female
☐ Transgender
☐ Non-Binary
☐ Prefer not to answer

7.2. What is your age?

☐ 18-24
☐ 25-34
☐ 35-44
☐ 45-54
☐ 55-64
☐ 65+

7.3. What is your marital status?

☐ Married
☐ Widowed
☐ Divorced
☐ Separated
☐ Never married

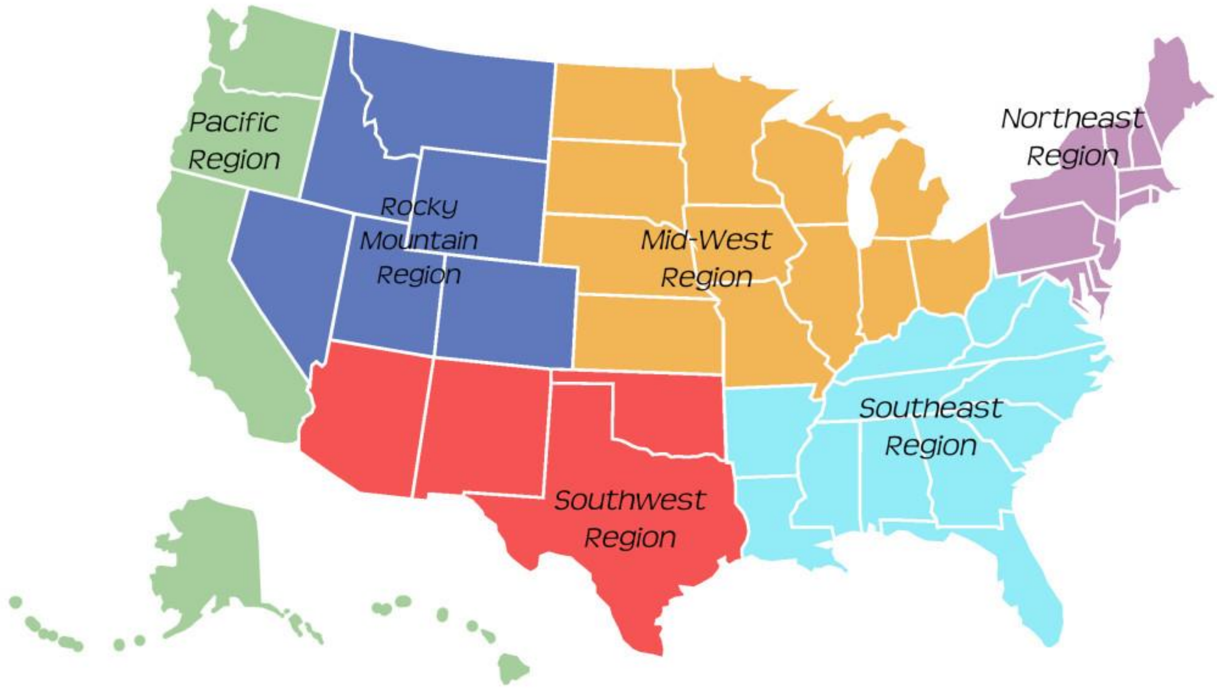
7.4. What is the highest level of education that you have completed?

☐ Less than high school
☐ High school graduate
☐ Some college
☐ 2-year degree
☐ 4-year degree
☐ Professional degree
☐ Doctorate

7.5. What is your current employment status?

☐ Employed full time
☐ Employed part time
☐ Unemployed looking for work
☐ Unemployed not looking for work
☐ Retired
☐ Student

7.6. Which region best describes where you currently reside?



☐ Pacific
☐ Rocky Mountain
☐ Mid-West
☐ Southwest
☐ Southeast
☐ Northeast

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VITA

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