A COMPREHENSIVE BEHAVIORAL STUDY ON LANE CHANGING MANEUVERS

by

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Abstract

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Since changing lanes might cause traffic congestion and car crashes, the investigation on different aspects of this behavior remains critical. In the past decades, most of lane changing behavior studies have continued to model this behavior mathematically. Lack of qualitative studies in traffic flow theory concepts, especially lane changing behavior is noticeable. This study tries to conduct a comprehensive view of lane changing behavior maneuvers with consideration and analysis the steps of the lane changing process. The author uses the mixed methodological approach to understand the factors which may cause drivers to change lane. After understanding the reasons that make drivers change lanes, the actions of vehicles which are involved in lane changing are investigated using naturalistic driving and stated preference data sets. The target vehicle (the vehicle which executes lane changing), the lag vehicle (the vehicle which is behind the target vehicle when lane changing is completed) and the lead vehicle (the vehicle which is in front of the target vehicle when lane changing is completed) are considered as the main vehicles which are involved in the lane changing maneuver. The stated and revealed preferences of drivers' actions when they are in target, lead and lag vehicle positions are

compared using statistical hypothesis tests. The application of this study is used for calibrating lane changing models. Lastly, this study introduces a methodological game theoretic model of merging and discretionary lane changing behavior. The lag and the target vehicles are considered as the main players of the game. The interactions of these players during the lane changing process is investigated with a game theoretical approach. This section of the study aims to introduce a more realistic model of merging and discretionary lane changing in a single framework which considers the actions of target and lag vehicle based on previous phase of the study. Overall, this dissertation explores lane changing behavior from the view of the decision-making process to introduce a joint merging and discretionary lane changing model.

Table of Contents

List of Illustrations

List of Tables

Chapter 1

Introduction

1.1 Overview of Study

Lane changing behavior represents a critical area of traffic flow theory research. Although many scholars have investigated lane changing behavior, some shortcomings still exist in this subject because lane changing remains a complex, two-dimensional process that involves many road users and stimuli. Discretionary lane changing appears particularly complex because it not only involves surrounding road users, but the reasons for the lane change itself; such as safety, environmental or traffic conditions, traffic law and various lane changing models. lane changing is one of the critical traffic behaviors which may cause congestion and car crashes and improving lane change behavioral studies such as understanding the decision-making process of drivers and modeling this behavior would yield in having more reliable traffic simulation results, making roads safer and saving peoples' lives . Therefore, this study conducts a comprehensive investigation of lane changing behavior, which includes understanding the causes of discretionary lane changes, the actions of drivers involved in the lane changing process and modeling lane changing behavior using a game theoretical approach. Figure 1-1 shows the sequence of the study steps.

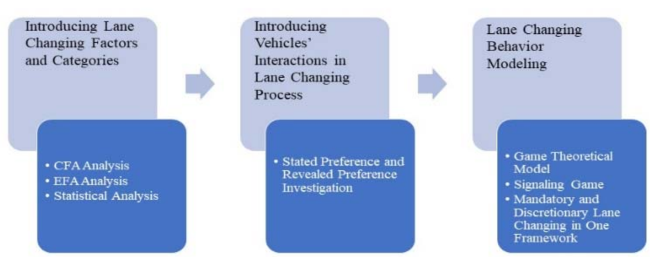


Figure 1-1. Sequence of Research

1.1.1. Background and Objectives of Study 1

In the past decades, many studies investigated the behavior of drivers make the decision to change lanes by developing mathematical models. However, fewer studies explored the decision-making and thinking process of drivers. In other words, the earlier studies to incorporate qualitative research methods failed as mathematical models. Some researchers attempted to understand drivers' attitudes during lane changing execution. For instance, *Keyvan-Ekbatani et al. (2016),* explored the perspective of drivers' lane changing behaviors using a two-stage test-drive. Subjects drove on a freeway with a camera equipped vehicle. Afterwards, the drivers explained their speed and lane choice decision while they watched the videos. This approach aimed to capture the drivers' thinking process during actual lane changing situations. The focus groups in the *Sun and Elefteriadou (2011)* study directed them to determine drivers' characteristics in lane changing models. Although this study investigated the drivers' decision-making process in different lane changing situations, it failed to explore the importance of general factors such as weather and drivers' moods. Moreover, *Knoop et al., (2018)* conducted an online survey to understand different drivers' lane change strategies on freeways. The online survey associated with this study helped the authors capture the perspective of drivers' lane changing behaviors in different situations; however, this dissertation investigates the reactions of drivers to specific stimuli rather than general factors that might affect their decisions to change lanes.

The previous studies of discretionary lane changing behavior fail to fully capture the stimuli that may trigger these discretionary events using qualitative methods. Understanding the reasons and the factors that cause drivers to change lanes may help in improving the safety of the roads, revising traffic laws, and enhancing discretionary lane changing models. The first phase of this research conducts a mixed methodological approach to identify all potential discretionary lane changing causes and determine their significance or importance.

1.1.2. Background and Objectives of Study 2

The purpose of the study is to understand the lane changing behavior sequence from the factors and reasons that cause drivers to change lanes. Previous lane changing studies have not considered obtaining the actions of driver who are involved in lane changing process. In the first phase, study introduced lane changing factors that cause drivers to change lane. After understanding the thought process of drivers regarding changing lanes, the second phase is intended to investigate the immediate decision of drivers in lane changing scenarios. Therefore, the author seeks to capture the anticipated actions of drivers involved in or impacted by the lane changing maneuver. Understanding the vehicles' actions in the lane changing process (Figure 1-2) remains critical for (1) developing lane changing models that consider the interactions of vehicles and (2) obtaining more reliable traffic simulation outcomes.

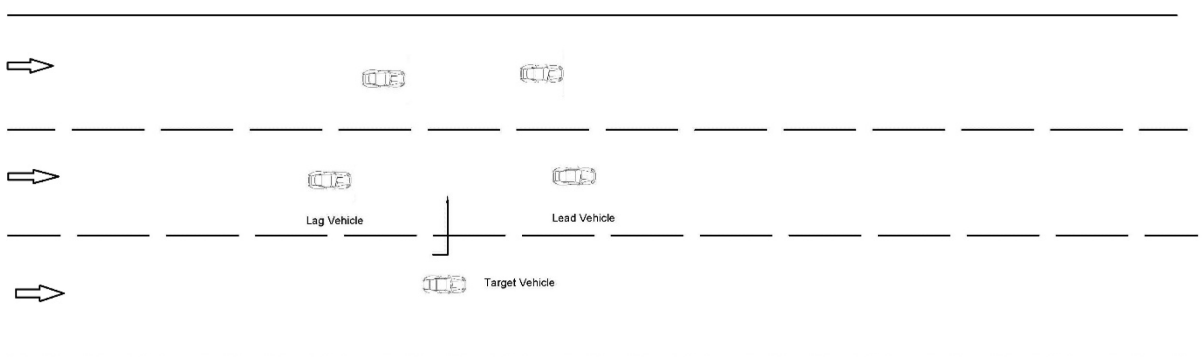


Figure 1-2. Lane Changing Process Players

Previously, studies such as Liu et al., 2007 and Talebpour et al.(2015a) have determined the actions of drivers' lane changes based on the scholars' knowledge; however, this study explores all possible actions of target, lead and lag vehicles based on both stated preference (SP) and revealed preference (RP) data sets. Focus groups and online surveys capture the participants anticipated behaviors or stated behavior. The observations of naturalistic lane changing behavior provide revealed behavior data. The author investigates the suitability of using SP data as a substitute for RP data. This requires comparing the observed driving behaviors with those derived from the SP survey. This investigation appears useful for determining data source requirements for developing realistic lane changing models and the suitability of SP data for developing lane changing models for autonomous vehicles.

1.1.3. Background and Objectives of Study 3

In this study, the researcher first determines the factors and categories which cause drivers to change lane. After understanding the reasons for lane changing, the potential actions of vehicles which are involved in lane changing is investigated. In the last phase, the researcher uses the outcomes of phase 2 of the study to develop a methodological lane changing model which can capture real-world lane-changing behavior more effectively. The author identifies the actions of vehicles involved in the lane changing process from the second study, then applies those outcomes to develop a game theoretical lane changing model.

Developing accurate driving behavior models remains critical for the simulation of real-world traffic behavior. For many decades, traffic scholars have been trying to improve lane changing models, but lane changing remains one of the most poorly understood components of traffic flow theory. Figure 1-3 summarizes the full range of lane changing models. Therefore, the author aims to employ the methodological approach for developing merging and discretionary lane changing behaviors model by considering (1) realistic scenarios for changing lanes and (2) broader traffic characteristics in the model. Moreover, the researcher tries to avoid nonsense assumptions. This developed methodological model generates a direction for improving the existing lane changing models.

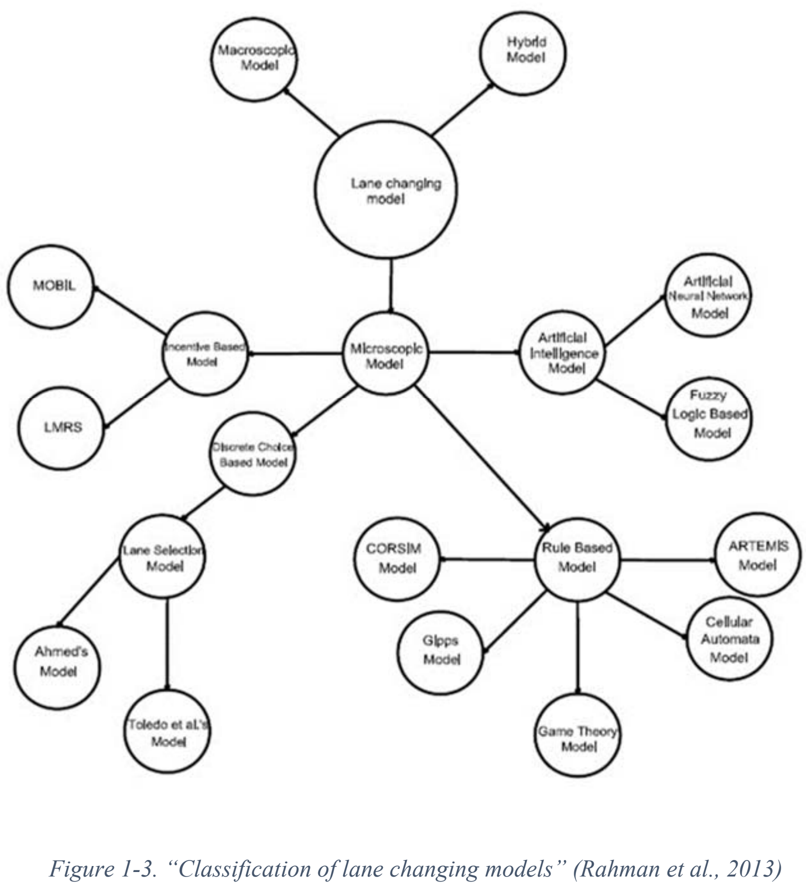


Figure 1-3. "Classification of lane changing models" (Rahman et al., 2013)

Drivers' behavior, especially in lane changing contains multiple interactions between drivers. The game theoretical approach is an optimization technique, which models the actions of different game players. In this study, the game theoretical approach models the actions of vehicles during lane changing. Previous studies *(Kita, 1999; Liu et al., 2007; Talebpour et al., 2015a; Wang et al., 2015*) use a game theoretical approach for modeling lane changing behavior, but this dissertation attempts to improve the methodology of these earlier models. This study models both merging and discretionary lane changing behaviors in one framework using a game theoretical approach. The target and lag vehicles, the main vehicles involved in lane changing process, represent the players in the developed game. Chapter 4 explains the full details of the game theoretical approach and the pay-off functions of the lane changing players.

Overall, this study represents a comprehensive view on lane changing behaviors and attempts to fill the gaps of lane changing studies that exist in the literature. The study begins with understanding the factors that cause discretionary lane changing and cluster those factors into different categories (Chapter 2). The study compares the actions of vehicles involved in the lane changing process using SP and RP data sets (Chapter 3). These first two phases use a mixed methodological approach. Lastly, the author models merging and discretionary lane changing behaviors using a game theoretical approach (Chapter 4). This study also opens new thoughts and directions for lane changing studies in the future research section of Chapter 5.

1.2 References

Keyvan-Ekbatani, M., Knoop, V.L., Daamen, W., 2016. Categorization of the lane change decision process on freeways. Transp. Res. Part C Emerg. Technol. 69, 515–526. https://doi.org/10.1016/j.trc.2015.11.012

Kita, H., 1999. A merging–giveway interaction model of cars in a merging section: a game theoretic analysis. Transp. Res. Part Policy Pract. 33, 305–312. https://doi.org/10.1016/S0965-8564(98)00039-1

Knoop, V.L., Keyvan-Ekbatani, M., de Baat, M., Taale, H., Hoogendoorn, S.P., 2018. Lane Change Behavior on Freeways: An Online Survey Using Video Clips [WWW Document]. J. Adv. Transp. https://doi.org/10.1155/2018/9236028

Liu, H., Xin, W., Adam, Z., Ban, X.J., 2007. A game theoretical approach for modelling merging and yielding behaviour at freeway on-ramp sections, in: 17th International Symposium on Transportation and Traffic Theory, London, UK.

Rahman, M., Chowdhury, M., Xie, Y., He, Y., 2013. Review of Microscopic Lane-Changing Models and Future Research Opportunities. IEEE Trans. Intell. Transp. Syst. 14, 1942–1956. https://doi.org/10.1109/TITS.2013.2272074

Sun, D., Elefteriadou, L., 2011. Lane-changing behavior on urban streets: A focus group-based study. Appl. Ergon. 42, 682–691. https://doi.org/10.1016/j.apergo.2010.11.001

Talebpour, A., Mahmassani, H.S., Hamdar, S.H., 2015. Modeling lane-changing behavior in a connected environment: A game theory approach. Transp. Res. Part C Emerg. Technol., Special Issue on International Symposium on Transportation and Traffic Theory 59, 216–232. https://doi.org/10.1016/j.trc.2015.07.007

Wang, M., Hoogendoorn, S.P., Daamen, W., van Arem, B., Happee, R., 2015. Game theoretic approach for predictive lane-changing and car-following control. Transp. Res. Part C Emerg. Technol. 58, Part A, 73–92. https://doi.org/10.1016/j.trc.2015.07.009

Chapter 2

Discretionary Lane Changing Stimuli Using Mixed Methodological Approach

2.1 Introduction

Studying lane changing behavior remains crucial in traffic flow theory because lane changes often create vehicle conflicts which may transform into crashes or create traffic flow turbulence when executed poorly by the drivers or vehicles involved. Numerous traffic factors such as following a slower vehicle or drivers' characteristics such as aggressive weaving impact lane changing behavior. Understanding the reasons behind lane changing behaviors may help highway designers, transportation planners, policy makers and other specialists to mitigate the risk and turbulence caused by lane changing. Furthermore, most lane changing models in microscopic traffic simulation software do not consider non-traditional elements such as weather, pavement condition or the emotions of drivers that result in a lane changing maneuver, so identifying the importance of these factors may allow developers to prioritize traffic simulation model improvements. The findings of this paper may also enhance lane changing modelling development in semi-autonomous vehicle environments by identifying user or driver expectations.

Few qualitative studies traffic flow theory concepts exist; this represents a significant research gap because people, and specifically drivers, seldom behave in an optimum manner. Therefore, traffic behavior models can be improved by identifying drivers' expectations or reactions to different stimuli in the driving environment. Since mathematical lane changing behavior models may be improved by recognizing the conditions necessary to prompt a lane changing maneuver, this research may help enhance the existing lane changing models. As more vehicles become equipped with levels 2, 3, and 4 autonomous features related to lane changing, driver expectations must be considered because drivers appear likely to discontinue use of specific features (even those that enhance safety) when they fail to provide the desired performance (*Knight, n.d.*).

The author use a mixed methodological approach of both qualitative (focus groups) and quantitative (online surveys) techniques to identify and analyze the factors that affect discretionary lane changing behavior. This strategy strengthens the research outcomes because it captures the perspectives and viewpoints of humans (qualitative phase) to identify the discretionary lane changing stimuli and data analysis (quantitative phase) their importance. Two different approaches are conducted in this study to analyze the survey's responses. First, Confirmatory Factor Analysis (CFA) is employed to investigate if the obtained lane changing factors from the focus groups are related to the potential lane changing latent variables which have been introduced in previous studies such as *(Dula and Geller, 2003; Hidas, 2002; Salvucci, n.d.; Sun and Kondyli, 2010; Toledo et al., 2003).* This part of the analysis is discussed in appendix C.

The investigation uses the survey results to rank the factors that trigger a discretionary lane change based on their importance using z-scores. Finally, the data driven approach for clustering lane changing factors using Exploratory Factor Analysis (EFA) is conducted in this study as well.

The outcomes of this research (1) may help policy makers create safer roads based on an improved understanding of discretionary lane changes and (2) may help traffic flow modelers develop discretionary lane changing models, which can include the identified factors and clusters.

The remainder of the paper includes a comprehensive literature review on previous qualitative studies in transportation engineering. Then, the paper discusses the data collection procedures, which include the methods of conducting the focus groups as well as the design and distribution of the surveys. After the author present the surveys' results and key findings, he present conclusions and recommend future research.

2.2 Literature Review

This study uses qualitative and quantitative research techniques such as focus groups and surveys to determine the most important factors that affect lane changing behavior. Consequently, the authors provide a review of existing lane changing models and applications of mixed methodological research approaches in the transportation engineering area.

Lane changing behavior has represented a field of interest for transportation scholars for decades. *Gipps (1986)* developed a lane changing model for urban areas where traffic signals, heavy vehicles and other obstructions may affect driving behavior. This model captured the hierarchy processes of lane changing and considers the actions drivers need to take during the maneuver. *Kesting, et al. (2007)*, developed a general model for merging and discretionary lane changing behaviors with the goal of minimizing overall braking induced by lane change (MOBIL); their model considered the impact of the utility of a given lane and the risk of lane changing on longitudinal accelerations. This model only operationally represented the last stage of lane changing behavior, and it cannot predict the strategic or tactical steps such as vehicle acceleration or deceleration during the lane changing process. *Hidas (2002)* also presented the model of cooperative lane changing and merging behaviors under congested situations for the Simulation of Intelligent TRAnsport Systems (SITRAS) model. This proposed model considers just the immediate leader and follower vehicles and not broader traffic characteristics such as lane density. *Li Gen et al. (2016)*, investigate the statistical characteristics of eight lane change elements. Based on this study, the parameters captured by vehicle trajectory data explain "the gaps, times to collision between vehicles and the merging vehicle's speed." *Schakel et al. (2012)*, developed an integrated lane changing behavior model that can be integrated with a car-following model and includes seven parameters that may impact the lane changing process. However, these models have not investigated the parameters that cause lane changing. *Balal et al. (2016)*, developed drivers' binary decision about executing or not executing a discretionary lane change using a Fuzzy Inference System (FIS) with four variables that describe the gaps between the preceding, following and target vehicles in the original and target lanes, but this model fails to consider driver characteristics. *Sun (2009)*, developed a lane changing probability model based on different lane changing scenarios and drivers' characteristics. This model may represent the real world in a more effective way since each model depends on the lane changing situation. *Choudhury et al. (2007),* developed a state dependency model for merging scenarios in congested traffic. This model indicates that the current decision making process of merging behavior depends on previous decisions. The model also can predict the future decision making process of a merging situation. However, this model just focuses on lateral decisions and excludes the longitudinal behaviors of cars.

Some studies investigate the advantages and disadvantages of different lane changing models. For instance, *Moridpour et al. (2013)*, explored the existing lane changing models in literature and investigated the strengths and weaknesses of each model. Their classification identifies two main categories of lane change behavior models, driving decision models and driving assistant models. *Ben-Akiva et al. (2006)* reviewed a series of advanced lane change models in order to propose more integrated driver behaviors. The reviewed models investigate the heterogeneity of the driver population and the correlation between a driver's decisions. *Rahman et al. (2013)* also reviewed and compared lane changing models related to microscopic traffic simulation. They investigated applicable improvements of lane changing models to make existing models more accurate.

Recent research on traffic behaviors includes lane changing and merging scenarios modelled using game theoretical approaches. *Kita (1999)* modeled the behavior of merging and through vehicles using game theory. In his model, both cars try to achieve the maximum benefit by predicting the other's behaviors; however, the pay-off function for the target and lag vehicles relies on minimizing the risk of lane changing (according to time to collision) and ignores other factors such as the speed gaining advantage for the target vehicle. *Liu et al. (2007)* also developed a vehicle interactions model for a merging situation using a game theory approach. Their game designates the freeway on-coming through vehicle and the on-ramp merging vehicle as players. The through vehicle tries to maintain its speed while the merging vehicle tries to enter the main lane as soon as possible. *Talebpour et al. (2015)* modeled merging and discretionary lane changing behaviors in one framework using a game theoretical approach. His model for discretionary lane changing evaluates the lane changing benefits based on acceleration to prevent collision and the speed gain after the maneuver. In this research, the lag vehicle (preceding vehicle in the target lane) also investigates whether to cooperate with the target vehicle or not. *Wang et al. (2015)* also proposed a lane change model that can be applied in connected and autonomous vehicle systems. They used dynamic game theory and receding horizon optimal control to develop a predictive method for lane changing and car following control. Overall, most game theory models in lane change behavior consider the typical factors that influence lane change such as speed gain. Some of the models even represent the behavior at the moment of the lane changing maneuver. For instance, they consider minimizing the risk of collision or keeping the current speed, so these models do not include the variables that cause lane changing.

The issues related to qualitative research include theoretical frameworks, data collection, management, and analysis. To increase the number and quality of qualitative research in the transportation area, scholars and researchers should appreciate and understand the importance of qualitative research (*Clifton and Handy, 2003)*. Based on previous qualitative research studies in transportation area, *Clifton and Handy (2003)* investigate the importance and challenges of conducting qualitative techniques such as focus groups, interviews or participant-observers in travel behavior research.

Surveys represent one of the most common qualitative research techniques to obtain people's points of view. *Rayle et al. (2016)* investigated the usage of "ridesourcing" in San Francisco such as who is using it, what are the reasons for using "ridesourcing" and how it is compared with taxis by distributing intercept surveys. Using surveys, the researchers evaluate the impact of "ridesourcing" on public transit and its compare travel time with taxis. *Golob and Regan (2001)* conducted a survey of 1200 trucking company managers in California to understand the effect of road congestion on truck operations. The surveys enabled this study to identify the trucking companies' responses and the factors that influence the response. *Agrawal et al. (2010)* investigated Californians' support or opposition to "green" transportation taxes and fees and mixed qualitative and quantitative analyses of the survey results to enhance research outcomes. *Yim et al. (2002)* conducted several behavioral surveys in San Francisco to evaluate the impacts of Intelligent Transportation Systems (ITS) on driving behavior. Drivers' behaviors at intersections depend on priority rules, the behavior of other road users and the intersection design. Similarly, *Björklund and Åberg (2005)* conducted a survey study to ask 1276 drivers (18-74 years old) to describe their yielding behavior in ten different cross sections to capture drivers' perspective on yielding situations. *Knoop et al. (2018)* conducted an online survey to understand different drivers' lane changing strategies and behavior on freeways. The online survey associated with this study helps the authors capture the perspective of drivers' lane change behavior in different situations; however, this study investigates the reactions of drivers during specific situations and not general factors that might affect their decisions to change lane. *Hayley et al., (2017)* investigate the role of driver emotional characteristics in risky driving behaviors. *Machado-León et al., (2016)* conducted a stated preference (SP) survey from 492 drivers to analyze the impacts of risky driving behaviors on drivers' perceptions of crash risk and to investigate differences in drivers' perceptions. Generally, previous studies show that conducting a qualitative study such as a survey may help researchers understand individuals' perceptions more effectively and identify factors that influence behavioral decision-making. Thus, mathematical models with supporting qualitative studies support appear more comprehensive than traditional models.

Focus groups represent another qualitative technique that helps scholars collect a specific target group's thinking process and opinions. In focus groups, people provide their opinions and discuss with each other the specific issues or contexts related to the research topic. *Flamm and Agrawal (2012)* conducted a variety of focus groups to identify the constraints that people face in buying "green" vehicles. The *Glasgow and Blakely (2000)* study coordinated different focus groups of older nonmetropolitan residents of upstate New York to understand transportation usage patterns in different stages of life. The focus groups provided the opportunity for older adults to talk about their transportation preferences. *Huth et al. (2014)* ran focus groups to identify differences in safety perceptions and concerns between motorcyclists and automobile drivers by investigating the risks of riding a motorcycle, and strategic and tactical challenges of motorcyclists. Most of the lane changing models in transportation literature use vehicle trajectories to develop and validate these models without assessing drivers' characteristics. However, the focus groups in the *Sun and Elefteriadou (2011)* study directed them to derive drivers' characteristics to consider in lane changing models. Overall, focus groups represent a valuable technique to solicit feedback from target populations about a specific issue, concern, or research question, which can improve models by implicitly and explicitly considering people's opinions.

In some studies, such as this paper, researchers organize both focus groups and surveys as a mixed methodological approach to reach their research goals. The *Kondyli and Elefteriadou, (2009)* study conducted three focus groups to explore drivers' attitudes and thinking processes in different congested and uncongested freeway ramp merging scenarios. The focus group discussions inform the importance of each lane changing factor. The *Ortúzar et al. (2000)* study conducted focus group and a household survey to determine whether bicycles can be used more often in Santiago as an alternative mode of transportation. These techniques provide a foundation for developing bicycle usage willingness models. *Stathopoulos et al. (2012)* explored innovative freight movement solutions in Rome by capturing stakeholders' and operators' opinions on behalf of carriers, retailers and own-account operators with focus groups and surveys. Obtaining stakeholders' opinions and feedback provided opportunities for enhancing freight policy design and analysis. *Fletcher et al. (2010)* also conducted three studies such as focus groups and surveys to understand the transportation gaps and the relationship of transportation access and economic outcomes in poor rural areas. The mixed methodological approach enables the research team to obtain and investigate multiple points of view.

Other mixed methods strategies exist in transportation research. For instance, *Keyvan-Ekbatani et al., (2016)* explored the perspective of drivers' lane changing behavior using a two-stage test-drive. Drivers had to drive on a freeway with a camera equipped vehicle. Next, drivers indicated the speed and lane choice decision while they watched the videos. This approach aims to capture drivers' thinking process during actual lane changing situations.

Overall, most qualitative studies investigate transportation planning rather than traffic flow theory concepts. In this paper, the authors use a mixed methodological research approach to determine the factors that prompt lane change maneuvers and behaviors, cluster these factors, determine the significance of each factor on its cluster, identify the importance of each category in the lane change execution and compare the lane change clusters.

This research seeks to provide a comprehensive identification of discretionary lane change stimuli and cluster these into categories with similar motivation. Moreover this study aims to identify the most important factors and clusters.

2.3 Methodology

This study seeks to determine the factors that influence lane change behavior, categorize the factors into different clusters, and identify their individual and cluster importance. To reach to these goals, the authors conduct a mixed methodological approach, which began with a qualitative data collection (three focus groups) and continues with quantitative methodology using online surveys (Tashakkori et al., 2003). In this study, the focus groups determine all potential lane changing reasons. The online survey provides the data to quantify and categorize the importance of the discretionary lane change stimuli. The surveys were distributed through Qualtrics, an Internet-based survey instrument.

2.3.1 Focus Groups

The research team conducted three focus groups to identify all potential lane changing reasons expressed by drivers. Consequently, they intuitively cluster these reasons into four categories. Table 2-1 shows the characteristics of the focus group participants.

Table 2-1. Characteristic of Focus Groups Participants

Participant ID	Age	Gender	Employment Status	Driving Experience on freeways in the US
Focus Group 1, #1	45-50	Male	Full time student	3 Years
Focus Group 1, #2	35-40	Male	Telecom Engineer	4 Years
Focus Group 1, #3	20-25	Male	Undergraduate Student	6 Years
Focus Group 1, #4	30-35	Female	Transportation Engineer	2 Years
Focus Group 1, #5	25-30	Female	College Student	1 Year
Focus Group 2, #1	25-30	Male	Full time student	2 Years
Focus Group 2, #2	25-30	Male	Full time student	2 Years
Focus Group 2, #3	30-35	Female	Freelancer (PhD in Marketing)	3 Years
Focus Group 2, #4	35-40	Male	Real Estate Agent	6 Years
Focus Group 3, #1	30-35	Male	Full time student	4 Yeas
Focus Group 3, #2	35-40	Female	Novel writer	4 Yeas
Focus Group 3, #3	20-25	Female	Transportation Engineer	7 Years
Focus Group 3, #4	25-30	Male	Vice principal of an elementary school	13 Years

Table 2-2 shows questions developed for the focus groups based on research team brainstorming and literature review.

Table 2-2. Focus Group Questions

Focus Group Questions
1-Warm up questions: Introduce yourself, what is your job? How frequently do you drive? What is your experience in driving?
2-Getting to the topic: Today we are going to talk about lane changing. Do you like lane changing or not? Because some drivers change lanes all the time. Some of them change lanes based on their situations and some conservative ones try not to change lanes at all unless they have to.
3-Lane changing moments: Would you please express your opinion about the following situations on freeway?
a- Trapped behind a slow vehicle.

b- Being behind a truck or bus. Does safety matter to you in this case?
c- Change lane in order to exit or enter to a freeway.
d- When congestion is seen downstream of your lane.
e- Change lane in order to gain speed.
f- How is your driving style? Do you enjoy the added excitement of going zig zag?
g- What happens if the adjacent lane has a better pavement condition?
h- What do you do if someone is tailgating you?
i- What is your reaction if another vehicle is coming to your lane without considering the available gap?
j- Does your vehicle condition affect your lane changing behavior?
k- Which behaviors of adjacent vehicles affect your lane changing behavior?
l- Can any distraction like listening to the radio or using your smart phone affect your lane changing behavior?
m- Do signs affect your lane changing behavior?
4-Imagine you are target, lead or lag vehicle, what will be your possible actions in in each case during lane changing process?
5-Do you have any comment or specific matter that you want to add to our conversation?

As specified earlier, the researchers used the focus groups to identify an exhaustive list of discretionary lane changing reasons (Table 2-3) and built different categories. The participants of the study were not aware of the authors' intention for categorizing lane changing reasons and only discussed the questions in Table 2-2. Table 2-3 shows the steps of focus groups analysis.

Table 2-3: Steps of focus groups analysis

Steps of focus groups analysis	
Step 1	Audio recordings of focus groups sessions
Step 2	Taking notes during focus groups sessions
Step 3	Listening to the recordings
Step 4	Taking comprehensive notes on participants' inputs
Step 5	Initial content analysis and placing factors in obtained categories found in literature
Step 6	Post content analysis by confirming themes and associated factors

2.3.1.1 Focus groups details and analysis

The researcher conducted three focus groups (five or six people in each) to obtain all potential reasons that cause drivers to change lane. The focus groups used structured, open-ended questions to capture participants' views and opinions about lane changing reasons. The focus group participants had driven for at least one year, had freeway driving experience and were older than 18 years old. Participant were recruited by email, which was approved by the University of Texas at Arlington Institutional Review Board. The invitees were selected from the researcher's personal social network; however, he attempted to maintain the heterogeneity of the focus groups participants by inviting people from different age groups, different genders, different occupations and different nationalities.

Each focus group lasted between 40 and 60 minutes. First, the researcher introduced himself; then, he asked the participants to introduce themselves as well as revealing their driving experience, especially on freeways. Afterwards, the warm-up question was asked (Table 2-2) regarding the general sense and feelings of the participants about lane changing behavior by asking "what comes to your mind when I ask you about changing lanes?". Finally, participants used multiple structured open-ended questions to capture the potential reasons that cause them to change lanes. Once saturation occurred in the discussion, the researcher continued the session with a new question. Lastly, the researcher asked the participants if they have any more input that they did not previously share. The audio of all focus groups was recorded for collecting data afterwards. The focus groups were discontinued after achieving a saturation in responses.

The investigators of this study used audio recordings to determine the themes and analyze the responses *(Greenwood et al., 2017)*. This type of focus group data analysis has the advantage of being cost effective and trustworthy compared to the traditional transcription analysis approach *(Greenwood et al., 2017)*. The authors reviewed the audio recordings carefully and collected the lane changing factors identified by participants shown in Table 2-4. The researcher took comprehensive notes on participant input and tried to place the lane changing stimuli into categories identified in previous studies. The two research team members confirmed the lane changing categories and associated lane changing factors to each category. All the categories of lane changing were obtained from previous studies such as *Dula and Geller, 2003; Hidas, 2005;*

Lei and Wu, 2007; Salvucci, n.d.; Sun and Kondyli, 2010; and Toledo et al., 2003. Table 2-4 shows the factors in each category for the CFA analysis (see appendix C for the analysis).

Table 2-4. Lane Changing Factors and Clusters

Category	Factor ID	Lane Changing Factor
Emotional	27	Distraction (Listening to the radio, using GPS, seeing billboards, talking on the phone, someone is talking to you, etc.)
	37	New car or smaller and more flexible car. (Type or model of the car matters)
	40	Good mood (e.g. listening to a music or being excited)
Environmental	17	Sharp curves
	21	Weaving, merging or diverging area
	22	Familiar with the road
	29	Seeing a police car. (e.g. police care with radar on the shoulder or police car moving in a freeway)
	30	Weather is rainy, snowy and windy
	31	Water accumulated in the right most lane
	34	Bad pavement condition or because the road is bumpy
	43	In response to more aggressive drivers such as New York or Mexico city
	46	Changing lane because the Following a car that produces lots of smoke and obstructs view
	51	People in another vehicle are fighting or crying. (You think their behavior might not be normal)
	53	Other people in your car request the lane change
	55	Lane blockage (e.g. stalled car in your lane)
Safety	16	Crossing a train track in order to be in a better and safe situation
	18	Curves in order to have more space and be safe
	23	Car is not in a good condition. (When car does not steer or brake well)
	25	Sleepy (e.g. in the morning when you go to work and you are sleepy)
	26	Car is parked or stopped on the shoulder
	28	Vehicle in front of you keeps braking or brakes for no reason
	32	Use the middle lane to avoid other vehicles' lane changing or merging
	36	Emergency vehicle is parked or stopped on the shoulder
	38	Object in your lane.(e.g. seeing a dead animal or a piece of lumber)

	41	Pass a truck or a heavy vehicle even if those vehicles go fast
	42	Truck or a heavy vehicle is beside you in the adjacent lane
	44	Avoid a road side hazard such as fire along one side of a road
	45	Somebody is tailgating you
	47	Provide the left lane for other vehicles to pass you
	48	Car is parked or stopped on the shoulder AND people are observed outside of the vehicle
	49	Trailing vehicle flashes its headlights
	50	Following vehicle with potentially insecure cargo like a mattress
	52	Sudden evasive action to shoulder of freeway or exit from freeway when something suddenly happens to your car
	54	Other driver is on the phone
Temporal	12	Expect to gain speed in adjacent lane
	15	Travel time constraint (being in a rush; need to be someplace soon (e.g. in the morning for going to work)).
	24	Night time
	33	Congestion downstream in your lane (Lane Density matters)
	35	Heavy traffic (in general)
	39	Use lane with truck prohibition

2.3.2 Survey Design

The authors designed a survey to determine the lane change factor load in order to determine the importance of each factor within its category as well as the importance of each category on lane changing execution. In the designed survey, the respondents ranked lane changing reasons using a Likert-type scale from 1 to 7, with 1 being strongly disagree to 7 being strongly agree, to identify the most important factors in the lane changing process. The surveys use random ordering of questions to eliminate order bias.

2.3.2.1 Sample characteristics

This study analyzed a sample of 220 responses. Of the entire participant sample, the greatest percentage of participants were aged 24 to 29 years old (24.1%). The majority of participants were female (85%) and Caucasian (81.4%). Nearly thirty-two percent (31.4%) had some college credit, no degree, and twenty (19.5%) were high school graduates. Fifty-three participants

(24.1%) had a college degree, and together approximately eight percent had a masters, professional, or doctorate degree. Fifty participants (22.7%) report an annual income of less than $15,000. Nearly half of the participants (45.5%) operate a sedan, with thirty percent of the participants owning their vehicle for between five to ten years. The majority (69.1%) of participants do not have a blind spot feature on their vehicle and have more than ten years of driving experience (63.6%) in the United States. More than half (52.7%) of the participants report driving on the freeway over two times per week. Table 2-4 shows the sample characteristics of all survey participants.

Table 2-5. Demographic Characteristics of Study Participants

Variable	Categories	N (%)
Age	18-23 years old	29 (13.2%)
	24-29 years old	53 (24.1%)
	30-35 years old	32 (14.5%)
	36-41 years old	35 (15.9%)
	42-47 years old	22 (10%)
	48 years old or older	49 (22.3%)
Gender	Male	33 (15%)
	Female	187 (85%)
	Prefer not to answer	(0)
Level of Education	Some high school, No diploma	12 (5.5%)
	HS graduate	43 (19.5%)
	Some college credit, No degree	69 (31.4%)
	Associates degree	26 (11.8%)
	Bachelors degree	53 (24.1%)
	Masters degree	13 (5.9%)
	Professional degree	2 (0.9%)
	Doctorate degree	2 (0.9%)
Variable	Categories	N (%)
Race	White or Caucasian	179 (81.4%)
	Black or African-American	24 (10.9%)
	American Indian or Alaska Native	0

	Asian	9 (4.1%)
	Native Hawaiian or Pacific Islander	0
	Other	8 (3.6%)
Annual Income	Less than $15,000	50 (22.7%)
	$16,000 to $25,000	23 (10.5%)
	$26,000 to $35,000	47 (21.4%)
	$36,000 to $45,000	24 (10.9%)
	$46,000 to $55,000	13 (5.9%)
	$56,000 to $65,000	26 (11.8%)
	More than $65,000	37 (16.8%)
Type of Vehicle	Sedan	100 (45.5%)
	Truck	19 (8.6%)
	SUV	77 (35%)
	Hatch-back	15 (6.8%)
	Full size van	9 (4.1%)
Age of Vehicle	Less than one year	29 (13.2%)
	1-3 years	41 (18.6%)
	3-5 years	35 (15.9%)
	5-10 years	65 (29.6%)
	10-20 years	40 (18.2%)
	Older than 20 years	10 (4.5%)
Car has Lane Departure/Blind spot Feature	Yes	68 (30.9%)
	No	152 (69.1%)
Years of Driving Experience in the US	Less than one year	0 (0%)
	1-5 years	46 (20.9%)
	5-10 years	34 (15.5%)
	More than 10 years	140 (63.6%)
Frequency of Driving on Freeway	More than two times per week	116 (52.7%)
	One or two times per week	47 (21.4%)
	One or two times per month	28 (12.7%)
	Once a month or less	29 (13.2%)

2.3.3 *Survey Analysis*

The analysis of lane changing factors survey includes three different steps:

- Determine (1) the load and importance of the factors within each latent variable (found in previous studies) using CFA and (2) the importance of each cluster in causing lane changing execution. The authors calculate the mean of each cluster for each subject to obtain the unique mean for each cluster. Due to the non-normal distribution of the data set, use a Kruskal-Wallis non-parametric statistic test and Dunn procedure to identify significant differences between the defined clusters (details of the analysis are shown in appendix C).
- Determine the most and the least important discretionary lane changing factors by generating z-scores in order to prioritize them for consideration for incorporation into simulation packages.
- Determine (1) the potential lane changing clusters with a data driven approach using EFA, (2) the appropriateness of using EFA, (3) number of required clusters (4) the importance of each factor within its cluster and (5) the importance of each data driven cluster in causing discretionary lane changes.

2.3.3.1 Prioritizing lane changing factors using Z-scores

This step analyzes all lane changing factors together to determine their importance. Since the designed survey uses a Likert scale a mean or standard deviation analysis across the different respondents represents an invalid approach for ranking the factors (*Bertram, n.d.*). Instead, this study normalizes the responses of each participant using z-scores ($(x-\mu)/\sigma$) across each respondent.

The author uses ($(x-\mu)/\sigma$) where μ and σ are the mean and standard deviation of each participants' responses to the questions (each participant had 40 questions to answer) to obtain the z-score for each participant response . Afterwards, the average of the z-scores are calculated for each lane changing factor using $\sum$(z-scores)/220. A larger z-score means that the drivers attribute a greater importance to this factor than other factors. Table 2-6 shows the lane changing factors based on their importance on causing drivers to change lane. For instance, "Changing lane because an emergency vehicle is parked or stopped on the shoulder" is the most important factor which in causing drivers to change lane. Therefore, the author prioritizes the lane changing factors using these z-scores.

Table 2-6:Prioritizing lane changing factors using z-scores

ID	Lane Changing Factors	Z-Scores
36	Changing lane because an emergency vehicle is parked or stopped on the shoulder	0.605
38	Changing lane because of object in your lane.(e.g. seeing a dead animal or a piece of lumber)	0.502
44	Changing lane to avoid a hazard such as fire along one side of a road	0.459
28	Changing lane because a vehicle in front of you keeps braking or brakes for no reason	0.414
48	Changing lane because a car is parked or stopped on the shoulder (because of having a flat tire or something is wrong with their cars) and people are observed outside of the vehicle	0.394
46	Changing lane because the car in front of you produces lots of smoke and blocks your view	0.353
52	Changing lane to go to shoulder of freeway or exit from freeway when something suddenly happens to your car	0.341
50	Changing lane if a truck with something in it like mattress is in front of you and you do not feel safe	0.331
55	Changing lane because of lane blockage (e.g. stalled car in your lane)	0.326
26	Changing lane because a car is parked or stopped on the shoulder	0.287
34	Changing lane because of bad pavement condition or because the road is bumpy	0.200
47	Changing lane to provide the left lane for other vehicles to pass you	0.193
45	Changing lane because somebody is tailgating you	0.181
16	Changing lane because of crossing a train track in order to be in a better and safe situation	0.159
29	Changing lane because of seeing a police car. (e.g. police care with radar on the shoulder or police car moving in a freeway)	0.156
31	Changing lane to avoid being in the right most lane when water is accumulated in that lane because of rain	0.153
18	Changing lane on curves in order to have more space and be safe	0.070
23	Changing lane when your car is not in a good condition. (When car does not steer or brake well)	0.000
32	Changing lane to the middle lane to avoid other vehicles' lane changing or merging	-0.065
54	Changing lane because another driver is on the phone	-0.065
51	Changing lane because people in another vehicle are fighting or crying. (You think their behavior might not be normal)	-0.072

33	Changing lane when there is congestion downstream in your lane (Lane Density matters)	-0.101
12	Changing lane in order to gain speed	-0.117
21	Changing lane because of being in weaving, merging or diverging area	-0.148
39	Changing lane for going to the lanes that are not allowed for trucks	-0.173
27	Changing lane because of any kind of distraction (Listening to the radio, using GPS, seeing billboards, talking on the phone, someone is talking to you, etc)	-0.174
22	Changing lane due to being familiar with the road	-0.175
15	Changing lane because of being in a rush; I need to be someplace soon (e.g. in the morning for going to work).	-0.182
35	Changing lane in heavy traffic	-0.198
30	Changing lane when the weather is rainy, snowy and windy	-0.202
53	Changing lane based on what other people in your car ask you to do	-0.205
25	Changing lane when sleepy (e.g. in the morning when you go to work and you are sleepy)	-0.222
17	Changing lane because there are a lot of sharp curves	-0.246
42	Changing lane when a truck or a heavy vehicle is beside you in the adjacent lane	-0.276
40	Changing lane because of having a good mood (e.g. listening to a music or being excited)	-0.281
49	Changing lane because a vehicle behind you flashes its headlights	-0.285
43	Changing lane in areas that drivers are more aggressive such as New York or Mexico city (Location matters)	-0.333
41	Changing lane in order to pass a truck or a heavy vehicle even if those vehicles go fast	-0.345
37	Changing lane with newer car or smaller and more flexible car. (Type or model of the car matters)	-0.491
24	Changing lane at night time	-0.766

The example of a z-score calculation as well as the table of all z-scores are brought in appendix E.

2.3.3.2 Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) represents a data driven approach to develop clusters of the discretionary lane change stimuli. The EFA uncovers the relationship of the different factors with a latent variable, develops a scale or subscale and identifies the underlying construct of the measured factors.

Factor analysis reduces large sets of variables by grouping them based on their strong inter correlations. Aside from a dimensionality reduction, EFA can be used to compress data and visualize highly dimensional datasets. The smaller groups consist of variables that have a strong linear correlations with each other. The results of factor analysis may differ from other data analysis techniques such as Principal Component Analysis (PCA) and Cluster Analysis (*Anand et al., 2014)*. Principal component analysis (PCA) converts a number of possibly correlated variables into a smaller number of variables, which are linearly uncorrelated.

Exploratory Factor Analysis (EFA) is a technique that, similar to Principal Component Analysis (PCA), is used to find the relationship between factors and reduce dimensionality of the factors. Unlike PCA, EFA is based on a common factor model which for instance, assumes that lane-changing factors can be assigned to a few clusters in a way that each factor is placed to a specific single cluster. In the end, EFA seeks to identify the common clusters and their relationship to the factors *(Anand et al., 2014)*. The selection of EFA and PCA depends on: "(1) the objectives of the factor analysis and (2) the amount of prior knowledge about the variance in the variables" *(Hair et al., 2014)*. PCA fits the majority of the original variances into the least possible number of clusters, whereas EFA seeks to identify what the variables (lane-changing factors) have in common *(Hair et al., 2014)*. Since this study uses the EFA technique because it wants to determine the factors that can represent a lane changing cluster.

$\xi 1$, $\xi 2$, … ξi, are a set of common clusters, X is a set of lane-changing factors, and δi is the specific cluster. There is no correlation between the clusters. An EFA model is shown below:

Eq 2-1. $$X_1 = \lambda_{11}\xi_1 + \lambda_{12}\xi_1 + \ldots + \lambda_{1c}\xi_1 + \delta_1$$

Eq 2-2. $$X_2 = \lambda_{21}\xi_1 + \lambda_{22}\xi_1 + \ldots + \lambda_{2c}\xi_1 + \delta_2$$

Eq 2-3. $$X_3 = \lambda_{31}\xi_1 + \lambda_{32}\xi_1 + \ldots + \lambda_{3c}\xi_1 + \delta_3$$

$$\vdots \qquad \vdots \qquad \vdots$$

Eq 2-4. $$X_n = \lambda_{n1}\xi_1 + \lambda_{n2}\xi_1 + \ldots + \lambda_{nc}\xi_1 + \delta_n$$

Here, each X represents the underlying cluster to the extent of λ. Therefore, the variance of X_i can be represented as follows: (ref)

Eq 2-5. $\mathrm{Var}(X_i) = \mathrm{Var}(\lambda_{12}\xi_1 + \delta_i) = \lambda_i^2 + \mathrm{Var}(\delta_i) = 1$

"Here λ_{i2} is called the communality of X_i" *(Anand et al., 2014)*. The term "factor loadings" describes the relation between the lane-changing factors and the clusters.

2.3.3.2.1 Validity of Exploratory Factor Analysis

The Bartlett test of sphericity can be used to determine if factor analysis is appropriate by examining the entire correlation matrix to determine correlation among variables (lane-changing factors). This index shows that at least a number of the variables in the matrix have significant correlations with each other so that the clustering approach can be proceed. Prior to using factor analysis, the existence of a structure needs to be supported by a "strong conceptual foundation"*(Hair et al., 2014)*. Clustering of the factors should proceed only if sufficient correlation among the variables (lane-changing factors) exists. Since Bartlett's test observes significant correlation among the variables (the p-value is <0.0001), clustering the lane changing factors appears reasonable.

2.3.3.2.2 Determining the appropriateness of EFA analysis using Kaiser-Meyer-Olkin measure of sampling adequacy

The measure of sampling adequacy can calculate the level of intercorrelations of the variables (lane-changing factors) and determine if factor analysis is appropriate for all factors. The measure ranges between 0 and 1 and is 1 when other variables predict each variable (lane-changing factor) without error. This measure provides the following interpretations:

> "0.80 or above, meritorious; 0.70 or above, middling; 0.60 or above, mediocre; 0.50 or above, miserable; and below 0.50, unacceptable" *(Hair et al., 2014)*

Each variable (lane-changing factor) must have a Measure of Sampling Adequacy (MSA) that is greater than 0.50 and if not, it should be removed one by one starting from the smallest. The overall test must have an MSA value that is greater than 0.5 as well *(Hair et al., 2014)*.

The results of the measure of sample adequacy shows that all of lane changing factors have a Kaiser-Meyer-Olkin measure of greater than 0.8 and the overall MSA of the EFA model is 0.89 which are shown in Table 2-7 Therefore, all lane changing factors should be kept for proceeding of clustering purpose.

Table 2-7:Results of Measure of Sample Adequacy

Lane Changing Factor ID	MSA	Lane Changing Factor ID	MSA	Lane Changing Factor ID	MSA	Lane Changing Factor ID	MSA
12	0.886	26	0.897	36	0.913	46	0.908
15	0.876	27	0.864	37	0.881	47	0.846
16	0.862	28	0.954	38	0.897	48	0.929
17	0.914	29	0.829	39	0.823	49	0.844
18	0.869	30	0.847	40	0.886	50	0.894
21	0.911	31	0.888	41	0.843	51	0.817
22	0.884	32	0.865	42	0.851	52	0.938
23	0.820	33	0.919	43	0.878	53	0.916
24	0.905	34	0.919	44	0.931	54	0.899
25	0.895	35	0.881	45	0.839	55	0.950
						KMO	**0.891**

2.3.3.2.3 Determining the number of clusters in Exploratory Factor Analysis

The Latent Root Criterion is the most common technique that can be applied to factor analysis in order to determine the number of clusters. The underlying logic is that each cluster should explain the variance of at least one lane-changing factor. In factor analysis, each cluster "contributes a value of 1 to the total eigenvalue" *(Hair et al., 2014)*. The eigenvalue can be reliably used to determine the number of clusters when the number of variables (lane-changing factors) is between 20 and 50 such that all the clusters with eigenvalues of less than 1 are disregarded and only the ones with an eigenvalue of greater than 1 are regarded as significant. In case the number of variables (lane-changing factors) is less than 20 or greater than 50, this method tends to produce too few or too many clusters respectively *(Hair et al., 2014)*. The results of the EFA analysis show that three latent variables should be considered for the clustering of lane changing factors because the first three latent variables have eigenvalues greater than 1. Table 2-8 shows the eigenvalues of potential clusters.

Table 2-8:Potential lane changing clusters and the associated eigen values

Potential Clusters	Eigenvalue
F1	9.907
F2	4.969

F3	1.108
F4	0.838
F5 . . .	0.787
F23	0.008

2.3.3.2.4 Identifying lane changing clusters using EFA technique

The previous analysis indicated that the forty different lane changing factors should be grouped into the three categories shown in Tables 2-9 to 2-11 The third column of this table shows the z-scores associated with each factor. The larger z-score indicates the more that factor importance in triggering a discretionary lane change. Based on EFA analysis outcomes, the author names the first cluster as “peripheral factors”, the second cluster as “subjective factors” and the third cluster as “temporal factors”. The “peripheral factors” represent the external reasons that can force drivers to initiate a discretionary lane change such as “Changing lane because a vehicle in front of you keeps braking or brakes for no reason”. However, the “subjective factors” represent situations that make the driver feel uncomfortable maintaining the current status such as “Changing lane because of crossing a train track in order to be in a better and safe situation ”. Finally, the “temporal factors” are the ones that are related to the matter of time such as “Changing lane because of being in a rush; I need to be someplace soon (e.g. in the morning for going to work)”. Tables 2-9 to 2-11 also show the average z-scores in each cluster. Based on the results, the “peripheral” cluster has the greatest z-score, which means this cluster generally causes drivers to changing lanes more than the other two clusters.

Table 2-9:Factors of “Peripheral” cluster

Factor ID	Factors in "Peripheral" cluster	z-scores
36	Changing lane because an emergency vehicle is parked or stopped on the shoulder	0.60
38	Changing lane because of object in your lane.(e.g. seeing a dead animal or a piece of lumber)	0.50
44	Changing lane to avoid a hazard such as fire along one side of a road	0.46

28	Changing lane because a vehicle in front of you keeps braking or brakes for no reason	0.41
48	Changing lane because a car is parked or stopped on the shoulder (because of having a flat tire or something is wrong with their cars) and people are observed outside of the vehicle	0.39
46	Changing lane because the car in front of you produces lots of smoke and blocks your view	0.35
52	Changing lane to go to shoulder of freeway or exit from freeway when something suddenly happens to your car	0.34
50	Changing lane if a truck with something in it like mattress is in front of you and you do not feel safe	0.33
55	Changing lane because of lane blockage (e.g. stalled car in your lane)	0.33
26	Changing lane because a car is parked or stopped on the shoulder	0.29
34	Changing lane because of bad pavement condition or because the road is bumpy	0.20
47	Changing lane to provide the left lane for other vehicles to pass you	0.19
45	Changing lane because somebody is tailgating you	0.18
31	Changing lane to avoid being in the right most lane when water is accumulated in that lane because of rain	0.15
54	Changing lane because another driver is on the phone	-0.07
33	Changing lane when there is congestion downstream in your lane (Lane Density matters)	-0.10
21	Changing lane because of being in weaving, merging or diverging area	-0.15
Average of z-scores		0.26

Table 2-10:Factors of "Subjective" cluster

Factor ID	Factors in "Subjective" cluster	Z-Scores
16	Changing lane because of crossing a train track in order to be in a better and safe situation	0.16
29	Changing lane because of seeing a police car. (e.g. police care with radar on the shoulder or police car moving in a freeway)	0.16
18	Changing lane on curves in order to have more space and be safe	0.07
32	Changing lane to the middle lane to avoid other vehicles' lane changing or merging	-0.07
51	Changing lane because people in another vehicle are fighting or crying. (You think their behavior might not be normal)	-0.07
39	Changing lane for going to the lanes that are not allowed for trucks	-0.17
27	Changing lane because of any kind of distraction (Listening to the radio, using GPS, seeing billboards, talking on the phone, someone is talking to you, etc)	-0.17
22	Changing lane due to being familiar with the road	-0.17
35	Changing lane in heavy traffic	-0.20
30	Changing lane when the weather is rainy, snowy and windy	-0.20
53	Changing lane based on what other people in your car ask you to do	-0.20
25	Changing lane when sleepy (e.g. in the morning when you go to work and you are sleepy)	-0.22
17	Changing lane because there are a lot of sharp curves	-0.25
42	Changing lane when a truck or a heavy vehicle is beside you in the adjacent lane	-0.28

40	Changing lane because of having a good mood (e.g. listening to a music or being excited)	-0.28
49	Changing lane because a vehicle behind you flashes its headlights	-0.28
41	Changing lane in order to pass a truck or a heavy vehicle even if those vehicles go fast	-0.35
37	Changing lane with newer car or smaller and more flexible car. (Type or model of the car matters)	-0.49
24	Changing lane at night time	-0.77
Average of z-scores		-0.20

Table 2-11:Factors of "Temporal" cluster

Factor ID	Factors in "Temporal" cluster	Z-Scores
23	Changing lane when your car is not in a good condition. (When car does not steer or brake well)	0.00
12	Changing lane in order to gain speed	-0.12
15	Changing lane because of being in a rush; I need to be someplace soon (e.g. in the morning for going to work).	-0.18
43	Changing lane in areas that drivers are more aggressive such as New York or Mexico city (Location matters)	-0.33
Average of z-scores		-0.16

2.3.3.2.5 Significant differences between EFA clusters

For conducting the significant difference between the lane changing clusters, two of each cluster were compared (based on their z-scores) with each other using two sample z-test. The interpretation of the test is as follows:

H_0: The difference between the means is equal to 0.

H_a: The difference between the means is lower than 0.

The results summarized in Table 2-12 show that mean of "peripheral" cluster is significantly greater than other two clusters (p-value<0.0001), but no significant difference between the means of the "subjective" and "temporal" clusters exists. Therefore, the "peripheral" cluster seems to cause more discretionary lane changes than the other two clusters.

Table 2-12:Summary of clusters' significance tests

Cluster Comparisons	p-value of z-test for two independent samples
Peripheral & Subjective	<0.0001
Temporal & Subjective	0.31
Peripheral & Temporal	<0.0001

2.4 Conclusion

Lane changing may cause car crashes and traffic congestions, so this traffic behavior is a critical study area in transportation science. Although numerous studies are conducted in this area, especially lane changing behavior models, but the gap on qualitative studies on lane changing behavior causes the lack of knowledge on reasons and factors that cause drivers to make lane changes.

Discretionary lane changing behaviors may be due to various reasons such as following a slower moving car. Some factors may also be related to only other drivers' characteristics such as driving zig-zag. Most of lane changing models in traffic simulator software do not consider the non-traditional elements such as weather, road situation or emotions of drivers that cause a discretionary lane changing maneuver, so capturing these factors may improve traffic simulation models as well as help road designers, policy makers and transportation planners to make the roads safer for all road users.

In this study, authors conducted a mixed methodological approach using hearing voices approach described by *Greenwood et al., (2017)* was used to derive forty different discretionary lane change stimuli.

The importance of lane changing factors, regardless of clusters was investigated by generating z-scores. The larger value of z-score shows the more importance of that factor in forcing drivers to change lane. The ranking of all lane changing factors based on z-scores is shown in table 2-6.

The data driven clustering of lane changing factors was also conducted using an EFA approach. Three different latent variables, "Peripheral factors", "Subjective factors" and "Temporal factors" are introduced as lane changing categories based on this analysis. The analysis of data driven clustering indicates that the *"Peripheral cluster"* and external reasons are more likely to cause drivers to change lane. The hypothesis tests showed that "Peripheral" cluster seems to cause drivers to change lane significantly more than other two clusters. The importance of each lane changing factor in each cluster was also determined using z-scores which are shown in Tables 2-9 to 2-11.

This aim of this study was to apply mixed methodological approach to understand the potential lane changing reasons and group them into different categories using Exploratory Factor Analysis (EFA). Clustering lane changing reasons would be critical in developing a comprehensive lane changing model. Furthermore, this study provides a path and understanding of lane changing reasons and clusters for developing a comprehensive lane change propensity scale development. Thus, a lane changing model would be improved by considering non-traditional elements such as the reasons identified in this study in the mathematical models. The outcomes of this study appear helpful for transportation modelers to understand the decision-making process of drivers more effectively.

These types of studies may always be improved by increasing the number of sample size, but the researcher was limited to certain amount of budget for recruiting the survey as well as the certain number of subjects approved by University of Texas at Arlington Institutional Review Board.

This study can be enhanced by conducting comprehensive steps for generating lane changing propensity measurement and propose a large-scale development for lane changing reasons. Thus, use the lane changing propensity scale development to improve lane changing models and make the roads safer for all users.

2.5 References

Agrawal, A.W., Dill, J., Nixon, H., 2010. Green transportation taxes and fees: A survey of public preferences in California. Transp. Res. Part Transp. Environ. 15, 189–196. https://doi.org/10.1016/j.trd.2009.11.003

Ahern, A.A., Tapley, N., 2008. The use of stated preference techniques to model modal choices on interurban trips in Ireland. Transp. Res. Part Policy Pract. 42, 15–27. https://doi.org/10.1016/j.tra.2007.06.005

Anand, S., Padmanabham, P., Govardhan, A., 2014. Application of Factor Analysis to k-means Clustering Algorithm on Transportation Data. https://doi.org/10.5120/16673-6677

Bajari, P., Hong, H., Ryan, S.P., 2010. Identification and Estimation of a Discrete Game of Complete Information. Econometrica 78, 1529–1568. https://doi.org/10.3982/ECTA5434

Balal, E., Cheu, R.L., Sarkodie-Gyan, T., 2016. A binary decision model for discretionary lane changing move based on fuzzy inference system. Transp. Res. Part C Emerg. Technol. 67, 47–61. https://doi.org/10.1016/j.trc.2016.02.009

Ben-Akiva, M.E., Choudhury, C., Toledo, T., 2006. Lane changing models, in: Proceedings of the International Symposium of Transport Simulation.

Bertram, D., n.d. Likert Scale \lick-urt\, n. 11.

Björklund, G.M., Åberg, L., 2005. Driver behaviour in intersections: Formal and informal traffic rules. Transp. Res. Part F Traffic Psychol. Behav. 8, 239–253. https://doi.org/10.1016/j.trf.2005.04.006

Bryant, F.B., Yarnold, P.R., Michelson, E.A., 1999. Statistical Methodology. Acad. Emerg. Med. 6, 54–66. https://doi.org/10.1111/j.1553-2712.1999.tb00096.x

Cao, X., Young, W., Sarvi, M., 2013. Exploring Duration of Lane Change Execution 17.

Choudhury, C., Ben-Akiva, M.E., Toledo, T., Rao, A., Lee, G., 2007. State dependence in lane changing models. Elsevier.

Clifton, K.J., Handy, S.L., 2003. Qualitative Methods in Travel Behaviour Research, in: Transport Survey Quality and Innovation. Emerald Group Publishing Limited, pp. 283–302. https://doi.org/10.1108/9781786359551-016

Coifman, B., Cassidy, M., 2002. Vehicle reidentification and travel time measurement on congested freeways. Transp. Res. Part Policy Pract. 36, 899–917. https://doi.org/10.1016/S0965-8564(01)00046-5

Collins, A., Rose, J., Hess, S., 2007. Stated Preference survey design in air travel choice behaviour modelling. Proc. Eur. Transp. Conf. 2007 HELD 17-19 Oct. 2007 LEIDEN Neth.

Dill, J., Voros, K., 2007. Factors Affecting Bicycling Demand: Initial Survey Findings from the Portland, Oregon, Region. Transp. Res. Rec. J. Transp. Res. Board 2031, 9–17. https://doi.org/10.3141/2031-02

Dula, C.S., Geller, E.S., 2003. Risky, aggressive, or emotional driving: Addressing the need for consistent communication in research. J. Safety Res. 34, 559–566. https://doi.org/10.1016/j.jsr.2003.03.004

Errampalli, M., Okushima, M., Akiyama, T., n.d. Lane Change Modelling with Fuzzy Logic in Microscopic Traffic Simulation 6.

Flamm, B.J., Agrawal, A.W., 2012. Constraints to green vehicle ownership: A focus group study. Transp. Res. Part Transp. Environ. 17, 108–115. https://doi.org/10.1016/j.trd.2011.09.013

Fletcher, C.N., Garasky, S.B., Jensen, H.H., Nielsen, R.B., 2010. Transportation Access: A Key Employment Barrier for Rural Low-Income Families. J. Poverty 14, 123–144. https://doi.org/10.1080/10875541003711581

Gan, H., Ye, X., 2012. Urban freeway user' diversion response to variable message sign displaying the travel time of both freeway and local street. IET Intell. Transp. Syst. 6, 78–86. https://doi.org/10.1049/iet-its.2011.0070

Gipps, P.G., 1986. A model for the structure of lane-changing decisions. Transp. Res. Part B Methodol. 20, 403–414. https://doi.org/10.1016/0191-2615(86)90012-3

Glasgow, N., Blakely, R.M., 2000. Older Nonmetropolitan Residents' Evaluations of Their Transportation Arrangements. J. Appl. Gerontol. 19, 95–116. https://doi.org/10.1177/073346480001900106

Golob, T.F., Regan, A.C., 2001. Impacts of highway congestion on freight operations: perceptions of trucking industry managers. Transp. Res. Part Policy Pract. 35, 577–599. https://doi.org/10.1016/S0965-8564(00)00008-2

Greenwood, M., Kendrick, T., Davies, H., Gill, F.J., 2017. Hearing voices: Comparing two methods for analysis of focus group data. Appl. Nurs. Res. ANR 35, 90–93. https://doi.org/10.1016/j.apnr.2017.02.024

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2014. Multivariate data analysis.

Hayley, A.C., Ridder, B. de, Stough, C., Ford, T.C., Downey, L.A., 2017. Emotional intelligence and risky driving behaviour in adults. Transp. Res. Part F Traffic Psychol. Behav. 49, 124–131. https://doi.org/10.1016/j.trf.2017.06.009

Hidas, P., 2005. Modelling vehicle interactions in microscopic simulation of merging and weaving. Transp. Res. Part C Emerg. Technol. 13, 37–62. https://doi.org/10.1016/j.trc.2004.12.003

Hidas, P., 2002. Modelling lane changing and merging in microscopic traffic simulation. Transp. Res. Part C Emerg. Technol. 10, 351–371. https://doi.org/10.1016/S0968-090X(02)00026-8

Huth, V., Füssl, E., Risser, R., 2014. Motorcycle riders' perceptions, attitudes and strategies: Findings from a focus group study. Transp. Res. Part F Traffic Psychol. Behav. 25, 74–85. https://doi.org/10.1016/j.trf.2014.05.004

k proportions test [WWW Document], n.d. . Xlstat Your Data Anal. Solut. URL https://www.xlstat.com/en/solutions/features/comparison-of-k-proportions (accessed 2.24.19).

Kesting, A., Treiber, M., Helbing, D., 2007. General Lane-Changing Model MOBIL for Car-Following Models. Transp. Res. Rec. J. Transp. Res. Board 1999, 86–94. https://doi.org/10.3141/1999-10

Keyvan-Ekbatani, M., Knoop, V.L., Daamen, W., 2016a. Categorization of the lane change decision process on freeways. Transp. Res. Part C Emerg. Technol. 69, 515–526. https://doi.org/10.1016/j.trc.2015.11.012

Keyvan-Ekbatani, M., Knoop, V.L., Daamen, W., 2016b. Categorization of the lane change decision process on freeways. Transp. Res. Part C Emerg. Technol. 69, 515–526. https://doi.org/10.1016/j.trc.2015.11.012

Kita, H., 1999. A merging–giveway interaction model of cars in a merging section: a game theoretic analysis. Transp. Res. Part Policy Pract. 33, 305–312. https://doi.org/10.1016/S0965-8564(98)00039-1

Knight, W., n.d. Why Cars Won't be Driverless Anytime Soon [WWW Document]. MIT Technol. Rev. URL https://www.technologyreview.com/s/513531/proceed-with-caution-toward-the-self-driving-car/ (accessed 9.23.18).

Knoop, V.L., Keyvan-Ekbatani, M., de Baat, M., Taale, H., Hoogendoorn, S.P., 2018. Lane Change Behavior on Freeways: An Online Survey Using Video Clips [WWW Document]. J. Adv. Transp. https://doi.org/10.1155/2018/9236028

Kondyli, A., Elefteriadou, L., 2011. Modeling Driver Behavior at Freeway-Ramp Merges. Transp. Res. Rec. J. Transp. Res. Board 2249, 29–37. https://doi.org/10.3141/2249-05

Kondyli, A., Elefteriadou, L., 2009. Driver Behavior at Freeway-Ramp Merging Areas. Transp. Res. Rec. J. Transp. Res. Board 2124, 157–166. https://doi.org/10.3141/2124-15

Kusuma, A., Liu, R., Choudhury, C., Montgomery, F., 2015. Lane-Changing Characteristics at Weaving Section. Presented at the Transportation Research Board 94th Annual MeetingTransportation Research Board.

Lei, P.-W., Wu, Q., 2007. Introduction to Structural Equation Modeling: Issues and Practical Considerations. Educ. Meas. Issues Pract. 26, 33–43. https://doi.org/10.1111/j.1745-3992.2007.00099.x

Li Gen, Sun Lu, Pan Yiyong, Yu Ye, n.d. Analysis of Merging Behavior Parameters Using NGSIM Data Sets. CICTP 2016, Proceedings. https://doi.org/10.1061/9780784479896.008

Li, Z., Hensher, D.A., 2012. Congestion charging and car use: A review of stated preference and opinion studies and market monitoring evidence. Transp. Policy, URBAN TRANSPORT INITIATIVES 20, 47–61. https://doi.org/10.1016/j.tranpol.2011.12.004

Liu, H., Xin, W., Adam, Z., Ban, X.J., 2007. A game theoretical approach for modelling merging and yielding behaviour at freeway on-ramp sections, in: 17th International Symposium on Transportation and Traffic Theory, London, UK.

Loo, B.P.Y., 2002. Role of Stated Preference Methods in Planning for Sustainable Urban Transportation: State of Practice and Future Prospects. J. Urban Plan. Dev. 128, 210–224. https://doi.org/10.1061/(ASCE)0733-9488(2002)128:4(210)

Machado-León, J.L., de Oña, J., de Oña, R., Eboli, L., Mazzulla, G., 2016. Socio-economic and driving experience factors affecting drivers' perceptions of traffic crash risk. Transp. Res. Part F Traffic Psychol. Behav. 37, 41–51. https://doi.org/10.1016/j.trf.2015.11.010

Marczak, F., Daamen, W., Buisson, C., 2013. Merging behaviour: Empirical comparison between two sites and new theory development. Transp. Res. Part C Emerg. Technol. 36, 530–546. https://doi.org/10.1016/j.trc.2013.07.007

Moridpour, S., Sarvi, M., Rose, G., 2013. Lane changing models: a critical review. Transp. Lett.

Ortúzar, J. de D., Iacobelli, A., Valeze, C., 2000. Estimating demand for a cycle-way network. Transp. Res. Part Policy Pract. 34, 353–373. https://doi.org/10.1016/S0965-8564(99)00040-3

Peeta, S., Ramos, J.L., 2006. Driver response to variable message signs-based traffic information. IEE Proc. - Intell. Transp. Syst. 153, 2. https://doi.org/10.1049/ip-its:20055012

Peeta, S., Zhang, P., Zhou, W., 2005. Behavior-based analysis of freeway car–truck interactions and related mitigation strategies. Transp. Res. Part B Methodol. 39, 417–451. https://doi.org/10.1016/j.trb.2004.06.002

Peng, J., Guo, Y., Fu, R., Yuan, W., Wang, C., 2015. Multi-parameter prediction of drivers' lane-changing behaviour with neural network model. Appl. Ergon. 50, 207–217. https://doi.org/10.1016/j.apergo.2015.03.017

Rahman, M., Chowdhury, M., Xie, Y., He, Y., 2013. Review of Microscopic Lane-Changing Models and Future Research Opportunities. IEEE Trans. Intell. Transp. Syst. 14, 1942–1956. https://doi.org/10.1109/TITS.2013.2272074

Rayle, L., Dai, D., Chan, N., Cervero, R., Shaheen, S., 2016. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transp. Policy 45, 168–178. https://doi.org/10.1016/j.tranpol.2015.10.004

Razo, M., Gao, S., 2013. A rank-dependent expected utility model for strategic route choice with stated preference data. Transp. Res. Part C Emerg. Technol., Selected papers from the Seventh Triennial Symposium on Transportation Analysis (TRISTAN VII) 27, 117–130. https://doi.org/10.1016/j.trc.2011.08.009

Razo, M., Gao, S., 2010. Strategic Thinking and Risk Attitudes in Route Choice. Transp. Res. Rec. J. Transp. Res. Board 2156, 28–35. https://doi.org/10.3141/2156-04

Salvucci, D.D., n.d. Inferring Driver Intent: A Case Study in Lane-Change Detection. Th Annu. Meet. 4.

Sarvi, M., Kuwahara, M., 2007. Microsimulation of Freeway Ramp Merging Processes Under Congested Traffic Conditions. IEEE Trans. Intell. Transp. Syst. 8, 470–479. https://doi.org/10.1109/TITS.2007.895305

Schakel, W., Knoop, V., van Arem, B., 2012. Integrated Lane Change Model with Relaxation and Synchronization. Transp. Res. Rec. J. Transp. Res. Board 2316, 47–57. https://doi.org/10.3141/2316-06

Stathopoulos, A., Valeri, E., Marcucci, E., 2012. Stakeholder reactions to urban freight policy innovation. J. Transp. Geogr., Special Section on Rail Transit Systems and High Speed Rail 22, 34–45. https://doi.org/10.1016/j.jtrangeo.2011.11.017

Stinson, M., Bhat, C., 2003. Commuter Bicyclist Route Choice: Analysis Using a Stated Preference Survey. Transp. Res. Rec. J. Transp. Res. Board 1828, 107–115. https://doi.org/10.3141/1828-13

Sun, Daniel(Jian), Elefteriadou, L., 2011. Lane-changing behavior on urban streets: A focus group-based study. Appl. Ergon. 42, 682–691. https://doi.org/10.1016/j.apergo.2010.11.001

Sun, Daniel, Elefteriadou, L., 2011. Information Categorization Based on Driver Behavior for Urban Lane-Changing Maneuvers. Transp. Res. Rec. J. Transp. Res. Board 2249, 89–94. https://doi.org/10.3141/2249-11

Sun, D., Elefteriadou, L., 2010. Research and Implementation of Lane-Changing Model Based on Driver Behavior. Transp. Res. Rec. J. Transp. Res. Board 2161, 1–10. https://doi.org/10.3141/2161-01

Sun, D. (Jian), Kondyli, A., 2010. Modeling Vehicle Interactions during Lane-Changing Behavior on Arterial Streets. Comput.-Aided Civ. Infrastruct. Eng. 25, 557–571. https://doi.org/10.1111/j.1467-8667.2010.00679.x

Sun, D.J., 2009. A lane-changing model for urban arterial streets (Ph.D.). University of Florida, United States -- Florida.

Svenson, A.L., Gawron, V.J., Brown, T., n.d. General Dynamics.

Talebpour, A., Mahmassani, H.S., Hamdar, S.H., 2015a. Modeling lane-changing behavior in a connected environment: A game theory approach. Transp. Res. Part C Emerg. Technol., Special Issue on International Symposium on Transportation and Traffic Theory 59, 216–232. https://doi.org/10.1016/j.trc.2015.07.007

Talebpour, A., Mahmassani, H.S., Hamdar, S.H., 2015b. Modeling lane-changing behavior in a connected environment: A game theory approach. Transp. Res. Procedia 7, 420–440.

Tashakkori, A., Teddlie, C., Teddlie, C.B., 2003. Handbook of Mixed Methods in Social & Behavioral Research. SAGE.

Toledo, T., Koutsopoulos, H.N., Ben-Akiva, M.E., 2003. Modeling Integrated Lane-Changing Behavior. Transp. Res. Rec. J. Transp. Res. Board 1857, 30–38. https://doi.org/10.3141/1857-04

Wagh, S.T., Razvi, N.A., 2016. Marascuilo Method of Multiple Comparisons (An Analytical Study of Caesarean Section Delivery) 3, 4.

Wang, M., Hoogendoorn, S.P., Daamen, W., van Arem, B., Happee, R., 2015. Game theoretic approach for predictive lane-changing and car-following control. Transp. Res. Part C Emerg. Technol. 58, Part A, 73–92. https://doi.org/10.1016/j.trc.2015.07.009

Wardman, M., 1988. A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour. J. Transp. Econ. Policy 22, 71–91.

Washbrook, K., Haider, W., Jaccard, M., 2006. Estimating commuter mode choice: A discrete choice analysis of the impact of road pricing and parking charges. Transportation 33, 621–639. https://doi.org/10.1007/s11116-005-5711-x

Yao, S., 2015. Game theoretical approach on vehicle-cyclist interaction analysis.

Yim, Y., Khattak, A., Raw, J., 2002. Traveler Response to New Dynamic Information Sources: Analyzing Corridor and Areawide Behavioral Surveys. Transp. Res. Rec. J. Transp. Res. Board 1803, 66–75. https://doi.org/10.3141/1803-10

Zhang, Z., n.d. Analysis of the Traffic Behavior Based on Game Theory, in: International Conference on Transportation Engineering 2009. American Society of Civil Engineers, pp. 501–506.

Chapter 3

Naturalistic Driving Versus Stated Behavior Data for Calibrating Lane Changing Models

3.1 Introduction

Although many researchers have studied lane changing behavior, few studies have investigated the actions of drivers involved in lane changing execution. Typically, the most important interaction during lane changing execution occurs between the target vehicle (the vehicle that aims to change lane), the lag vehicle (the vehicle which is behind the target vehicle after lane changing) and the lead vehicle (the vehicle which is in front of the target vehicle after lane changing). The interactions of these vehicles, shown in Figure 3-1, remain critical during the lane changing process and they can affect driver safety. The (Liu et al., 2007) and (Talebpour et al., 2015a) studies have assumed actions for the vehicles involved in lane changing execution; however, they fail to validate these assumptions with naturalistic driving data. This study compares the results from a survey where subjects provide stated behavior data related to lane changing with naturalistic lane changing behavior to determine if survey data can serve as a suitable substitute for naturalistic driving data when calibrating simulation models.

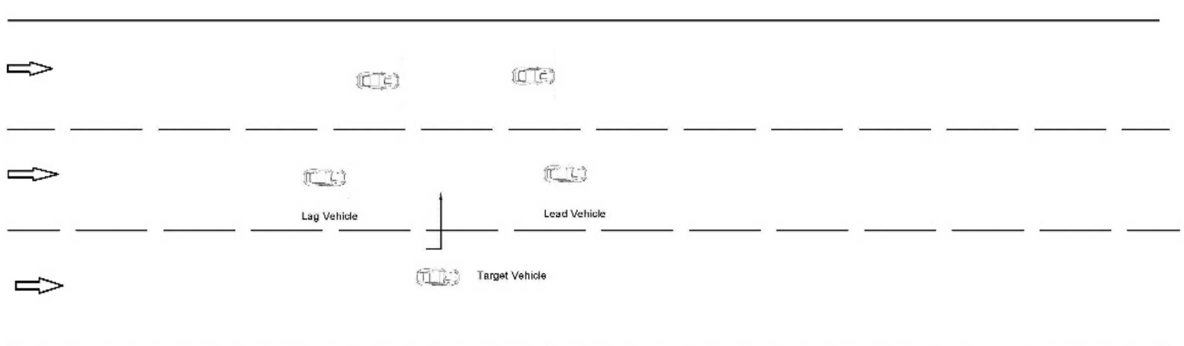


Figure 3-1. Vehicles Interactions in Lane Changing Process

Lane changing behavior studies need to be improved by considering the decision-process of drivers into mathematical modelling approaches. In the existing studies, scholars either use their own perspectives about lane changing to determine driver actions or choose logical and obvious constraints to lane changing execution (Kita, 1999; Liu et al., 2007; Talebpour et al., 2015a) for lane changing mathematical modelling. However, they do not consider the decision-making process of drivers. Considering vehicles’ actions during the lane changing process remains critical for building a foundation for developing lane changing models which consider vehicles’ interactions. Therefore, this study aims to understand the decision-process and preference of drivers’ actions in lane changing maneuver using mixed methodological approach. The authors first ran three focus groups to capture all potential actions of drivers as lead, lag and target vehicles. Afterwards an online survey conducted to specify the significant actions of drivers as lead, lag and target vehicles in four different lane changing situations as “Uncongested-Merging”, “Uncongested-Discretionary”, “Congested-Merging” and “Congested-Discretionary” which are shown in Figure 3-2.

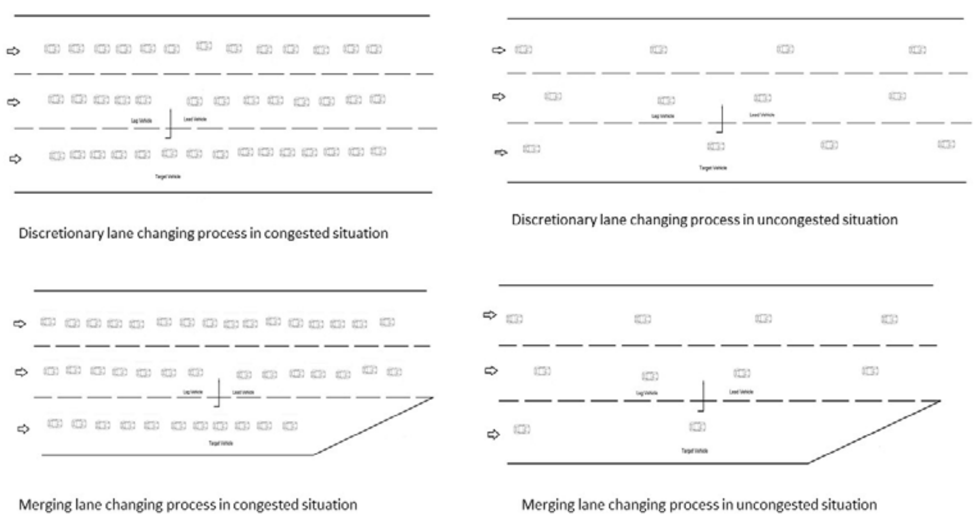


Figure 3-2. Different Lane Changing Situations

While collecting stated driving behavior data may be the least costly and readily available strategy for gathering the necessary information to calibrate lane changing models, its validity requires comparison with real-world driver actions. Two common techniques exist for obtaining revealed driving behavior. First, trajectory data sets such as Next Generation SIMulation (NGSIM) data can be used where changes in the speeds and microscopic traffic flow parameters of all vehicles involved in the lane change can be captured; however, trajectory data remains difficult to capture in public data sets and a limited number of trajectory data sets currently exist. A second method relies on observing the naturalistic driving behaviors during lane changing.

Extracting the actions of lead and lag vehicle behaviors in lane changing situation from video recordings remains much easier than available trajectory data sets, because capturing the subject vehicle velocity does not require additional data processing when using particular data collection applications. However, deriving the velocity and behavior of the surrounding vehicles from video data seems impossible without advanced video processing software; therefore, this study conducts video recording of naturalistic driving behavior to capture the revealed preference of the subject vehicle in the lead, lag and target vehicle roles but excludes other vehicle actions. The authors capture the different lane changing behaviors of drivers as shown in Figure 3-2. The data collection section discusses the details of the data collection.

This study explores the consistency between the stated preference (SP) and revealed preference (RP) of drivers' actions during lane changing execution. The remainder of this manuscript includes transportation studies that have conducted stated preference techniques, video-recording observation as revealed preference and studies that compared SP and RP data, the data collection process, the methodology, findings and conclusion.

3.2 Literature Review

This study compares survey collected SP data and video-recorded naturalistic RP data for driver interactions during discretionary and merging lane changing. The review of literature explores previous studies using SP surveys and on-board video collection for RP. The authors also investigate previous transportation studies that compare SP and RP behaviors.

3.2.1 Background of Stated Preference Techniques in Transportation Studies

The review of previous studies indicates that previous studies frequently use SP survey to investigate route choice, transportation planning and variable message signs(VMS). The *Razo and Gao (2013)* study conducted a SP survey that concentrates on strategic route choice where users arrange their trips based on future traffic conditions. Stinson and Bhat (2003) also developed a SP survey to investigate the route level (e.g., travel time) and link-level (e.g., pavement quality) factor importance for influencing commuter bicyclists' route choices. *Collins et al. (2007)* studied air travel behavior choice modelling using different SP approaches; they compared and contrasted the outcomes of traditional SP techniques versus the actual online booking of users. Moreover, another study conducted a SP survey to select route links under different scenarios to obtain the route choice behavior in networks which contain risky travel times and real-time information *(Razo and Gao, 2010)*. Many transportation scholars use SP surveys to assess driver response to VMSs. The driver response models to VMSs developed by *Peeta and Ramos (2006)* used an on-site survey, a mail-back survey and an Internet-based survey. The *Gan and Ye (2012)* study also designed an on-site SP survey to collect freeway users' response to variable message signs called D-VMS which shows the travel time of urban freeways and local streets. Other transportation planning studies often use SP surveys to answer research questions. In a discrete choice experiment (DCE) designed by *Washbrook et al., (2006)*, the 548 commuters' opinions who drive to work lonely were collected in order to predict commuter mode choice behavior in response to specific policies such as road pricing or parking charges. Another study introduces SP techniques with the four step model to improve the urban transportation planning process *(Loo, 2002)*.

The *Kondyli and Elefteriadou, (2009)* study recognizes that the drivers' thinking process rarely receives consideration in gap acceptance and lane changing models; therefore, they conducted three focus groups to identify drivers' decision and thinking process while merging on freeway-ramps. A previous study by *Sun and Elefteriadou, (2011)* conducted focus groups using a SP technique to capture "driver-related information" in order to consider drivers' characteristics in lane changing models. The *Knoop et al., (2018)* research also carried out an online survey to ask drivers about their lane changing behavior action by showing video clips and investigate the relationship between lane changes and their speed choice.

Dill and Voros, (2007) used a random phone SP survey of adults to determine "the relationship between levels of cycling and demographics, objective environmental factors, perceptions of the environment, and attitudes." *Peeta et al., (2005)* deployed a survey to obtain non-truck drivers' socioeconomic characteristics and situational factors that influence their discomfort level when they are driving near trucks because they wanted to model the behavior of non-truck drivers and acquire the car-truck interactions based on quantifying their time dependent "discomfort level."

This paper conducted four online surveys to obtain the SP of drivers' actions as target, lead and lag vehicles in four different traffic and geometry conditions, which are shown in Figures 3-2.

3.2.2 Background on Studies Employed Video Recording Data Sets as Revealed Preference Data

Many studies have collected travel behavior data via video recording to model, calibrate and understand driver behavior. In this section, the authors review lane changing and merging studies that use video recording to collect naturalistic driving behavior data.

The *Keyvan-Ekbatani et al., (2016)* study recorded the lane changing behavior of drivers and asked them about their behaviors afterwards to explore the decision making process of drivers about lane and speed choices at the time of lane changing execution. However, this study uses video recordings to investigate the actions (accelerating decelerating, etc.) of vehicles involved in lane changing maneuver. *Cao et al., (2013)* used video recording data to analyze the lane changing execution duration for different conflicts between the target vehicle and the surrounding vehicles. *Kusuma et al., (2015)* employed loop detector and video recording data sets to develop an empirical analysis of lane changing behavior in weaving areas. Another study by *Marczak et al., (2013)* used video recording data collected by helicopter to investigate merging behavior on a motorway in the Netherlands and France. *Sarvi and Kuwahara, (2007)* used video recording data to capture the drivers' behaviors such as "zone definition, drivers' interaction, and the driver decision process" and develop a microsimulation program for investigating the process of freeway ramp merging in congested traffic situations. *Kondyli and Elefteriadou, (2011)* used video recording and focus groups data to develop a gap acceptance model under various merging situations, which estimated the vehicle interactions during merging. In another similar study, *Sun and Kondyli, (2010)* collected video recordings to differentiate lane changes between free, forced, and competitive/cooperative lane changing situations and quantified the vehicle interactions during lane changing execution. *Hidas, (2005)* also classified merging and weaving maneuvers as free, forced and cooperative lane changing behaviors using video data to model lane changing behavior. *Peng et al., (2015)* developed a neural network model for predicting lane changing behavior using real world road experiment and video recording data. As discussed in these previous studies, naturalistic driving data represents a common approach for understanding the real-world actions of drivers. This study also employs video recording data sets for capturing revealed preferences of drivers in lane changing situations.

Other studies gathered video recording data to calibrate and validate lane changing behavior models. For instance, one study developed a lane changing model with consideration of uncertainties associated with the modelling and validated it with video recording data *Errampalli et al., (n.d.)*.

Based on its frequent use in previous studies, video recording represents a common method for gathering real world lane changing behavior data. Therefore, this study also uses video recording to capture revealed preference of drivers' interactions with each other while changing lanes.

3.2.3 The Background on Comparison of Stated Preference and Revealed Preference on Traffic Studies

Some research studies compared the relationship between RP and SP data; however, only a few traffic studies conducted this type of comparison. The *Wardman, (1988)* paper investigates the process and methods for comparing SP and RP travel behavior. Another study by *Li and Hensher, (2012)* compared the SP opinions of people about congestion pricing and the associated behavioral RP and concluded that SP represent the real-world data well. Lastly, *Ahern and Tapley, (2008)* compared the SP and RP of passengers on using interurban rail and bus modes and investigated the pooling of these preferences to enjoy the benefits of both SP and RP data.

Based on the literature review, no previous studies SP and RP behaviors for lane changing; therefore, the contribution of this study provides a significant contribution by investigating the similarities and differences between the RP and SP behaviors. The outcomes of this research provide a foundation for more realistic modeling of lane changing behavior.

3.3 Data Collection

This paper's data collection process contains three different phases. First this research invites different subjects who have had driving experience on freeways to participate in the focus groups and indicate their potential actions as target, lead and lag vehicles roles.Second, the study designs an online survey for each traffic (uncongested and congested) and geometry (discretionary and merging) combination (four total). After cleaning the data, the team collected 60 responses for each combination other than the uncongested and merging case, which contained only 40 respondents (20 responses for uncongested-merging were omitted due to being incomplete). For each situation, the survey provided the figure associated with that case (see Figure 3-2) and asked the respondents to provide their potential actions as the target, lead and lag vehicles. The respondents can select multiple actions as their frequent lane changing behavior in the target, lead and lag vehicle roles. Although the pictures used do not exactly represent these conditions (congested, uncongested….) in a completely realistic manner, they can still provide a queue to the participants.

The third phase collects revealed preference data using video-recording. The researchers use the "AutoBoy BlackBox" Android application (Figure 3-3) for recording the drivers' behavior because it can record a vehicle's speed while taking a video of traffic ahead. The application records videos with the instantaneous speed of the subject vehicle shown in the video (Figure 3-4).

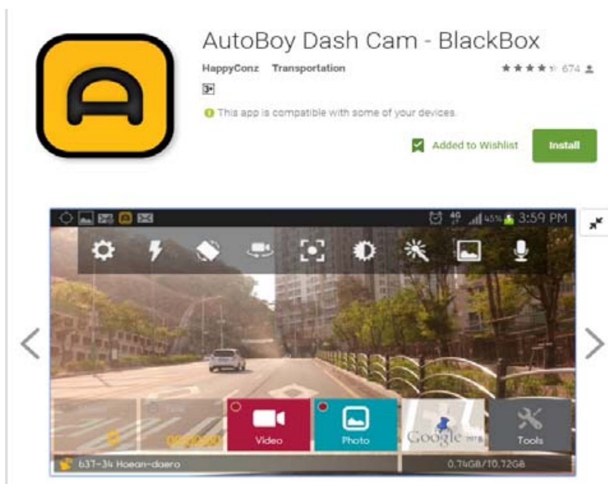


Figure 3-3. "AutoBoy BlackBox" Android Application ("DashCam app AutoBoy BlackBox night time interior filming possible solution," n.d.)

Figure 3-4. Video Recording of "AutoBoy BlackBox" Android Application

This feature of the application captures the driver's action (accelerating, decelerating, and keeping current speed). The study records the behaviors of nine subjects for each traffic situation (congested and uncongested).

Each subject might be the lane changing player (target or lag vehicles) and the vehicles in front of them (lead vehicles) multiple times. The subjects follow a prescribed route identified in Figure 3-5 along I-30, President George Bush Turnpike and I-20 in the Dallas-Fort Worth area. The congested traffic observations occurred from 7:30 a.m. to 8:30 a.m. or 5 p.m. to 6 p.m., which represents the peak hours in these areas. The researchers collected the uncongested traffic cases from 11 a.m. to 12 p.m. and 12 p.m. to 1 p.m. while traffic remains at a level of service of A or B. Each observation period lasts fifteen to forty-five minutes.

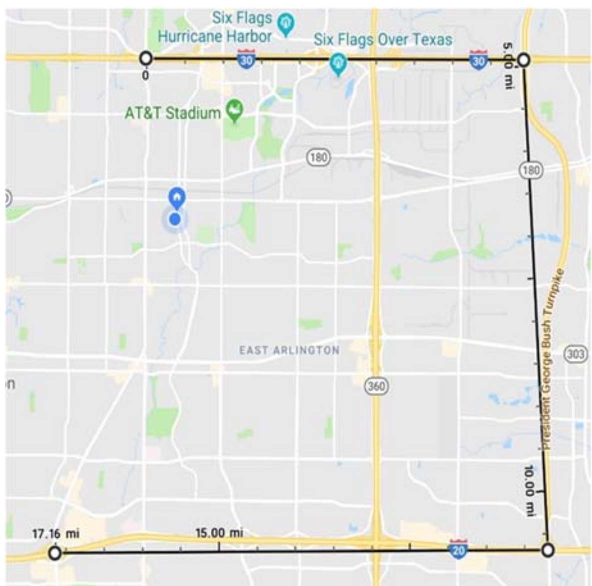


Figure 3-5. Route for Recording Revealed Preference Data

All on-ramp and lane-drop situations where people had to change lane were considered as merging scenarios and all other lane changings were considered as discretionary. Also, if the speed was below 40 mph the situation was considered congested and above 40 mph, the situation was considered as uncongested *(Coifman and Cassidy, 2002)*.

The authors revisited the recorded videos and watched them carefully to obtain the actions of each driver as the target and lag vehicles as well as the behaviors of lead vehicles in the four different traffic and geometry cases. If an uncongested situation occurred during peak hours, those data were recorded as uncongested data and vice versa.

The actions of the target, lead and lag vehicles were collected by observing the vehicle behavior (Appendix G) and watching the recorded videos.

3.3.1 Inclusion/exclusion criteria of drivers for real-world observation

The inclusion criteria of drivers for the real-world observation include:

1- Having a valid U.S. driving license.
2- Older than 21.
3- Having 0 or 1 car crashes in the past five years.
4- Not taking medications which cause drowsiness.
5- No discomfort driving on freeways in urban areas for up to an hour.
6- No safety concerns about driving a 2018 Toyota Camry.

3.4 Methodology

This study compares the SP and RP of drivers' actions as target, lead and lag vehicles in different lane changing situations. To pursue this goal, the authors conduct three different phases.

1- The first step uses a mixed methods approach (focus groups and online surveys) to obtain the SP of lane changing behaviors. First, the focus groups determine the potential actions of drivers (Table 3-1) as the target, lead and lag vehicles. The online surveys collect the actions of subjects in the different roles in lane changing execution. The researchers use a chi-square tests to identify any significant differences between (1) the each action of the lead, target and lag vehicles in the four different traffic and geometry cases and (2) the actions of each specific lane changing player (target, lead and lag vehicles).

2- The second step analyzes the RP of drivers' behaviors using video-recordings. After observing the lane changing behavior of drivers on freeway, the study follows the same procedure as the first step to identify any significant difference between (1) the each action of lead, target and lag vehicles in the four different traffic and geometry cases and (2) the actions of each specific lane changing player (target, lead and lag vehicles) under real-world observation.

3- Step 3 discusses the SP and RP perspectives of drivers in lane changing behavior situations.

3.4.1 Focus groups details and analysis

The researcher conducted two focus groups (five or six people in each) to obtain all potential actions of drivers as target, lead and lag vehicles. The focus groups utilized specific questions to fulfill the research questions. The participants of the focus groups had to have driving experience of at least one year, experience driving on freeways and be greater than 18 years old. The University of Texas at Arlington Institutional Review Board approved the recruitment of participants by an invitation email. The researcher tried to consider the heterogeneity of focus groups participants by inviting people from different age groups, different genders, different occupations and different nationalities. Table 3-1 shows the steps of focus groups analysis.

Table 3-1: Steps of focus groups analysis

Steps of focus groups analysis	
Step 1	Audio recordings of focus groups sessions
Step 2	Taking notes during focus groups sessions
Step 3	Listening to the audios
Step 4	Taking a comprehensive note on inputs of participants
Step 5	Initial content analysis and placing potential actions in their roles as target, lead and lag vehicles
Step 6	Post content analysis by confirming themes (different vehicles involved in lane changing process) and associated vehicles actions

In each focus group, five or six people were involved with consideration of heterogeneity of participants. The research showed Figure 3-1 to participants, described the roles of the target, lead and lag vehicles in lane changing process and asked them about their lane changing behaviors as drivers in the aforementioned positions. The themes of these focus groups were the potential actions of vehicles who are involved in the lane changing process. The researcher attempted to specify the potential actions of each vehicle based on participants' inputs.

The following statements show one verbatim example for each action of the target, lead and lag vehicles from the focus group discussions.

- "I usually speed and change lane" a participant talks from target vehicle perspective.

- “I am trying to give enough time to lag vehicle to see my signal” a participant talks from target vehicle perspective.
- “I try to slow down and let someone in” a participant talks from lag vehicle perspective.
- “Someone so not allow you to change lane and they go faster” a participant talks from lag vehicle perspective.
- “I maintain my speed & they should go faster to get in front of me” a participant talks from lag vehicle perspective.
- “If I see someone in front of me and they want to take left, I would change lane because I do not want to slow down” a participant talks from lag vehicle perspective.
- “I usually maintain what I am doing & they should go slower to get behind me” a participant talks from lead vehicle perspective.
- “I speed if the target vehicle forces to come my lane” a participant talks from lead vehicle perspective.
- “I do not care what is happening behind me” a participant talks from lead vehicle perspective.
- “If I am lead vehicle and someone is slowing down, I take signal and change the lane” a participant talks from lead vehicle perspective.

Therefore, all potential actions of drivers in different positions were captured.

The audio of all focus groups was recorded for collecting data afterwards. The focus groups were discontinued after achieving saturation in responses.

Finally, the researcher listened carefully to the audio recordings of focus groups and took comprehensive notes on the opinions of people regarding their behaviors as the target, lead and lag vehicles. The derived actions of vehicles were confirmed by two members of research team. The outcomes of the focus groups is a list of potential actions of the target, lead and lag vehicles shown in Table 3-2. One action of the lead vehicle (decelerating) from a previous study *(Svenson et al., n.d.)* is added to the list of vehicles’ actions in order to have a potential comprehensive list of target, lead and lag vehicles’ actions.

Table 3-2:Actions of Lane Changing Process Players

Driver	Actions of Drivers
Lag Vehicle	Yield for target vehicle
	Accelerate in order to prevent lane changing process happen
	Keep your speed
	Also you may change lane
Target Vehicle	Change lane aggressively without checking whether acceptable gap exist or not
	Waiting for an acceptable gap, then change lane
Lead Vehicle	Accelerate in order to help target vehicle to come to your lane
	Decelerate in order to prevent lane changing happen
	Keep your speed
	Change lane
	You do not care about what happens behind you

3.4.2 Analysis of Stated Preference Surveys

The researchers investigate if the action of vehicles involved in lane changing execution significantly differs under the four different geometry and traffic cases. The chi-square test compares different distributions of data sets to determine if at least one proportion is different from another. The authors seek to identify any significant differences in the SP actions of the target, lead and lag vehicles in the four specified cases. The test is interpreted:

H_0: The proportions are equal.

H_a: At least one proportion is different from another.

The authors use a significance level of 0.05 to reject or accept the null hypothesis (H_0).

The authors also conduct a z-test and chi-square test to explore if any significant difference exists between the SP actions of each vehicle involved (target, lead and lag vehicles) in lane changing execution.

3.4.2.1 Comparison of Target Vehicle Actions (SP)

Table 3-3 shows the results for the target vehicle action of change lane. The test fails to reject the null hypothesis; therefore, the distribution of the change lane appears similar for all four cases. A larger sample size may change the result of the analysis.

Table 3-3. Chi-square Test on "Change Lane" Action of Target Vehicle (SP)

Sample	Proportion of Changing Lane	Hypothesis Test		
CM	0.13	Chi-square test	Chi-square (Observed value)	1.78
CD	0.19		Chi-square (Critical value)	7.76
UM	0.20		DF	3.00
UD	0.23		p-value	0.62

Since the target vehicle can take only two actions, the same results occur for "do not change lane and wait for another acceptable gap." This result indicates that the SP of changing lanes as a target vehicle does not depend on the different traffic and geometry situations and they usually wait for an acceptable gap to change lane. The proportion changing lanes remains less than 25% in all cases.

3.4.2.2 Comparison of Lead Vehicle Actions (SP)

The lead vehicle has five possible actions:

- Accelerate in order to help target vehicle to come to your lane
- Decelerate in order to prevent lane changing happen
- Keep speed
- Change lane
- You do not care about what happens behind you

The study applies the same statistical method for these actions under the four cases. Table 3-4 summarizes the results of the chi-square test for all lead vehicle actions. The hypothesis tests indicate that lead vehicle's actions appear similar for all four cases, and the sample size appears sufficient because the p-values for each action remain large. This result indicates that geometry and traffic do not impact lead vehicle behavior. In all cases, less than eight percent of the subjects choose the action of "You do not care about what happens behind you," which means people mostly believe they have some awareness of the lane changings that occur behind them. The lead vehicle drivers state that they most accelerate to cooperate in lane changing execution or keep their current speed.

Table 3-4. Chi-square test on Actions of Lead Vehicle (SP)

Lead Vehicle: Accelerating (Cooperating)				
Sample	Proportion	Hypothesis Test		
CM	0.33	Chi-square test	Chi-square (Observed value)	0.62
CD	0.29		Chi-square (Critical value)	8.01
UM	0.27		DF	3.00
UD	0.31		p-value	0.89
Lead Vehicle: Decelerating (Closing the Gap)				
Sample	Proportion	Hypothesis Test		
CM	0.08	Chi-square test	Chi-square (Observed value)	2.84
CD	0.17		Chi-square (Critical value)	7.54
UM	0.13		DF	3.00
UD	0.17		p-value	0.43
Lead Vehicle: Keep Current Speed				
Sample	Proportion	Hypothesis Test		
CM	0.39	Chi-square test	Chi-square (Observed value)	1.24
CD	0.37		Chi-square (Critical value)	7.79
UM	0.35		DF	3.00
UD	0.31		p-value	0.75
Lead Vehicle: Changing Lane				
Sample	Proportion	Hypothesis Test		
CM	0.13	Chi-square test	Chi-square (Observed value)	2.86
CD	0.14		Chi-square (Critical value)	7.81
UM	0.23		DF	3.00

UD	0.15		p-value	0.41
Lead Vehicle: Do Not Care about Behind the Vehicle				
Sample	Proportion	Hypothesis Test		
CM	0.07	Chi-square test	Chi-square (Observed value)	3.28
CD	0.03		Chi-square (Critical value)	7.46
UM	0.02		DF	3.00
UD	0.07		p-value	0.35

3.4.2.3 Comparison of Lag Vehicle Actions (SP)

The lag vehicle has four possible actions:

- Yield for target vehicle
- Accelerate in order to prevent lane change
- Keep speed
- Also change lanes

The study applies the chi-square test to identify any significant differences between the four cases for each action. Table 3-5 summarizes the results of chi-square test for all actions of a lag vehicle. The hypothesis tests indicate that lag vehicle's actions appear similar for all four cases and do not depend on traffic and geometry conditions. A larger sample size may change the result of the analysis for the decelerating and changing lane actions; however, only the other actions appear unlikely to change with a larger sample due to their high p-value. The lag vehicle drivers most frequently decelerate to cooperate with the target vehicle to change lanes.

Table 3-5. Chi-square test on Actions of Lag Vehicle (SP)

Lag Vehicle: Decelerating (Cooperating)				
Sample	Proportion	Hypothesis Test		
CM	0.43	Chi-square test	Chi-square (Observed value)	3.68
CD	0.54		Chi-square (Critical value)	7.81
UM	0.53		DF	3.00
UD	0.41		p-value	0.30

Lag Vehicle: Accelerating (Closing the Gap)				
Sample	Proportion	Hypothesis Test		
CM	0.12	Chi-square test	Chi-square (Observed value)	2.07
CD	0.12		Chi-square (Critical value)	7.81
UM	0.13		DF	3.00
UD	0.19		p-value	0.56
Lag Vehicle: Keep Current Speed				
Sample	Proportion	Hypothesis Test		
CM	0.25	Chi-square test	Chi-square (Observed value)	1.89
CD	0.25		Chi-square (Critical value)	7.81
UM	0.17		DF	3.00
UD	0.19		p-value	0.60
Lag Vehicle: Changing Lane				
Sample	Proportion	Hypothesis Test		
CM	0.21	Chi-square test	Chi-square (Observed value)	5.02
CD	0.09		Chi-square (Critical value)	7.65
UM	0.17		DF	3.00
UD	0.21		p-value	0.17

3.4.3 Analysis of Action of Vehicles Involved in Lane Changing Execution (SP)

The outcomes of previous tests reveal that the SP of drivers' actions as target, lead and lag vehicles do not seem to significantly depend on either traffic or geometry conditions. Therefore, the study pools all four surveys' responses together into a sample of 220 responses to identify any significant differences among the probabilities for the actions associated with each vehicle involved in lane changing execution. The analysis of next step is based on the sample of all 220 responses.

The study tests differences in the probabilities of the actions of the target, lead and lag vehicles using the previously described Chi-square test. When a significant difference exists, the researchers conduct the Marascuilo procedure *(Wagh and Razvi, 2016)* to identify the specific actions that appear significantly different ("k proportions test," n.d.).

3.4.3.1 Analysis of Target Vehicle Actions (SP)

The researchers use a z-test to determine if no difference exists between the proportions of the two actions. The test interpretation is:

H_0: The difference between the proportions is equal to 0.

H_a: The difference between the proportions is different from 0.

The z-test shows a significant difference (p-value<0.0001) between "changing lane aggressively" and "waiting for an acceptable gap" exists with about 81% of the subjects waiting for an acceptable gap.

3.4.3.2 Analysis of Lead Vehicle Actions (SP)

The study uses the Chi-square test to identify any significant differences between the proportions of the lead vehicle's actions. The test interpretation is:

H_0: The proportions are equal.

H_a: At least one proportion is different from another.

The Chi-Square hypothesis test output shown in Table 3-6 confirms that at least one action has a proportion different from another lead vehicle action.

Table 3-6. Chi-square test for Comparison of Lead Vehicle Actions

Chi-square (Observed value)	114.233
Chi-square (Critical value)	9.488
DF	4
p-value	< 0.0001
alpha	0.05

The Marascuilo procedure (Table 3-7) identifies the source of difference between the lead vehicle's actions. The Marascuilo procedure identifies the significant differences between the action probabilities or proportions (part 1) and combines actions into similar groups (part 2). The lead vehicle actions of "decelerate in order to prevent lane changing happen" (option 2) and "change lane" (option 4) have similar probabilities and represent group B. Group C contains the lead vehicle actions of "Accelerate in order to help target vehicle to come to your lane" (option

1) and “Keep your speed” (option 3). The probabilities associated with the actions in these groups remain significantly different from the actions within the other groups. Overall, the proportions of responses show that the lead vehicle’s drivers seek to maintain their current speed or cooperate most frequently. Only a few respondents (6%) indicate that they do not care about lane changing behind them.

Table 3-7. Marascuilo procedure on Lead Vehicle’s Options

Marascuilo procedure				
Part 1				
Contrast	Value	Critical value	Significant	
|p(Option 1) - p(Option 2)|	0.200	0.127	Yes	
|p(Option 1) - p(Option 3)|	0.068	0.144	No	
|p(Option 1) - p(Option 4)|	0.177	0.130	Yes	
|p(Option 1) - p(Option 5)|	0.314	0.112	Yes	
|p(Option 2) - p(Option 3)|	0.268	0.130	Yes	
|p(Option 2) - p(Option 4)|	0.023	0.114	No	
|p(Option 2) - p(Option 5)|	0.114	0.093	Yes	
|p(Option 3) - p(Option 4)|	0.245	0.132	Yes	
|p(Option 3) - p(Option 5)|	0.382	0.114	Yes	
|p(Option 4) - p(Option 5)|	0.136	0.096	Yes	
Part 2				
Sample	Proportion	Groups		
Option 5	0.059	A		
Option 2	0.173		B	
Option 4	0.195		B	
Option 1	0.373			C
Option 3	0.441			C

3.4.3.3 Analysis of Lag Vehicle Actions (SP)

The study uses the Chi-square test to identify any significant differences between the proportions of the lag vehicle’s actions. The test interpretation is:

H_0: The proportions are equal.

H_a: At least one proportion is different from another.

The Chi-Square hypothesis test output shown in Table 3-8 confirms that at least one action has a proportion different from another lag vehicle action.

Table 3-8. Chi-square test for Comparison of Lag Vehicle Actions

Chi-square (Observed value)	114.010
Chi-square (Critical value)	7.690
DF	3
p-value	< 0.0001
alpha	0.05

The Marascuilo procedure (Table 3-9) for the lag vehicle indicates that the yield action occurs significantly more often than the other three lag vehicle actions that may apparently be grouped together with similar proportions. Almost sixty percent of the subjects indicate that they will yield to the target vehicle and cooperate.

Table 3-9. Marascuilo procedure on Lag Vehicle's Options

Marascuilo procedure			
Part 1			
Contrast	Value	Critical value	Significant
|p(Option 1) - p(Option 2)|	0.423	0.117	Yes
|p(Option 1) - p(Option 3)|	0.327	0.125	Yes
|p(Option 1) - p(Option 4)|	0.382	0.121	Yes
|p(Option 2) - p(Option 3)|	0.095	0.110	No
|p(Option 2) - p(Option 4)|	0.041	0.105	No
|p(Option 3) - p(Option 4)|	0.055	0.114	No
Part 2			
Sample	Proportion	Groups	
Option 2	0.173	A	
Option 4	0.214	A	
Option 3	0.268	A	
Option 1	0.595		B

3.4.4 *Analysis of Revealed Preference Data*

The study compares the naturalistic actions of drivers in the target, lead and lag vehicle roles situations using Chi-Square hypothesis test. The test interpretation is:

H_0: The proportions are equal.

H_a: At least one proportion is different from another.

The authors use a significance level of 0.05 to reject or accept the null hypothesis (H_0). The authors also conduct a z-test and chi-square test to explore if any significant difference exists between the RP actions of each vehicle involved (target, lead and lag vehicles) in lane changing execution. Table 3-10 shows the frequencies of lane changing vehicles' actions observed in naturalistic driving data collection. The congestion level and the description merging/discretionary lane changing scenarios are described in the following sections.

Table 3-10. Frequencies of Lane Changing Vehicles' Actions in RP

Target Vehicle	Uncongested-Merging	Uncongested-Discretionary	Congested-Merging	Congested-Discretionary
Option 1	20	42	6	16
Option 2	13	38	17	20
Total	33	80	23	36
Lead Vehicle	Uncongested-Merging	Uncongested-Discretionary	Congested-Merging	Congested-Discretionary
Option 1	4	18	2	4
Option 2	0	1	2	3
Option 3	4	39	7	20
Option 4	1	57	1	2
Total	9	65	12	29
Lag Vehicle	Uncongested-Merging	Uncongested-Discretionary	Congested-Merging	Congested-Discretionary
Option 1	5	12	11	17

Option 2	0	2	2	4
Option 3	12	43	8	5
Option 4	1	4	0	0
Total	18	61	21	26

3.4.4.1 Definitions of congested/ uncongested and merging/discretionary conditions

Based on traffic flow theory models such as *"Greenshield, Greenberg, Underwood, Edie-Underwood, Drake, Heat flow model"* shown in table 3-11 the lane density and speed has a reverse relationship with each other (**u** is the speed and **k** is the lane density). Therefore, if the speed decreases, the lane density increases and the spacing between the vehicles decreases as well. The lane changing behaviors in congested situations were collected in peak-hours (7:30 to 8:30 a.m. and 5:00 to 6:00 p.m.), so as a sample of different occasions the speed of vehicles were between 10 mph and 25 mph (lane density increases and spacing of vehicles decreases). Also, the observations of lane changing behaviors in uncongested situations were recorded in off-peak hours (11:00 to 12:00 p.m. and 12:00 to 1:00 p.m.) where the speed of vehicles were between 45 mph to 70 mph (lane density decreases and spacing of vehicles increases).

Table 3-11: Lane Density-Speed Relationship of Traffic Flow Models

Traffic Flow Models	Lane Density-Speed	Type of Relationship Between Lane Density & Speed
Greenshield Model	$u = u_f \times \left(1 - \frac{k}{k_j}\right)$	Reverse Relationship
Greenberg Model	$u = \lambda \times ln\left(\frac{k_j}{k}\right)$	
Underwood Model	$k = k_C \times ln\left(\frac{u_f}{u}\right)$	
Edie-Underwood	$u = u_f \times e^{\frac{k}{k_c}}$	
Drake Model	$u = u_f \times e^{-0.5\times\left(\frac{k}{k_c}\right)^2}$	
Heat Flow Model	$k = \frac{1}{L + C_1 u + C_2 u^2}$	

The speed of below 40 mph was considered as congested and above 40 mph was considered as uncongested conditions. Using speed as a proxy for representation of congested situation is not unprecedented in the literature *(Coifman and Cassidy, 2002)*.

Also in order to show the validity of the criteria the researcher calculates the spacing (figure..) of five vehicles for a sample of five cases and obtain the average of spacing in both congested and uncongested situations. Based on Texas Department of Transportation: (Citation here)

- If the spacing of vehicles is below 175 feet the road is congested.
- If the spacing of vehicles is between 175 to 350 feet, the road is moderately congested.
- If the spacing of vehicles is above 350 feet the road is uncongested.

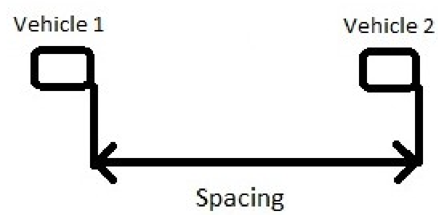


Figure 3-6:Spacing of vehicles

Table 3-12 summarizes the calculations of vehicles' spacing as well as the average of spacing in both congested and uncongested situations. The distance of spacing was calculated by freezing the screen on two different moments. The results show that the average of spacing in congested situations is 76.1 feet and 377.2 feet in uncongested conditions which confirm that the selected route was congested during peak hours and uncongested during off-peak hours.

Table 3-12:Sample of vehicles' spacing in congested and uncongested situations

Congested situations				Uncongested situations			
	Speed (mph)	Time (s)	Spacing (ft)		speed (mph)	Time (s)	Spacing (ft)
Case 1	23.6	3	103.3	Case 1	56.5	5	415
Case 2	24.85	2	72.8	Case 2	55.3	6	486.5
Case 3	11.18	3	49.2	Case 3	57.8	3	256
Case 4	23.6	3	103.3	Case 4	64.6	3	285.5
Case 5	11.8	3	52.2	Case 5	59.7	5	443
Average of spacing		**76.16**		Average of spacing		**377.2**	

The on-ramp merging situations were considered as merging lane changing situation and all other lane changing maneuvers were considered as discretionary lane changings.

3.4.4.2 Influences of Different Drivers on Lane changing Behaviors

In this section the joint probability of behavior for each individual in each role by each case. Then the revealed preference average behavior of the people is determined by calculating the average probabilities of each action taken by individuals. Table 3-13 summarizes these calculations. As an example, imagine:

Subject 1 has the following actions frequencies:

Target vehicle(Action 1)= 5 times

Target vehicle(Action 2)= 2 times

So the probability of behavior for each individual in each role is as follows:

Target p(action 1) = 5/7=0.71

Target p(action 2) = 2/7=0.29

Table 3-13:Probability of behavior for each individual in each role by each case

Proportions of actions	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Sub 6	Sub 7	Sub 8	Sub 9	Sub 10	Sub 11	Sub 12	Sub 13	Sub 14	Sub 15	Sub 16	Sub 17	Sub 18	Average of probability of actions
P(action 1 target)	0.71	0.20	0.50	0.57	0.13	0.50	0.29	0.30	0.63	0.90	0.25	0.42	0.50	0.67	0.60	0.78	0.90	0.00	0.49
P(action 2 target)	0.29	0.80	0.50	0.43	0.88	0.50	0.71	0.70	0.38	0.10	0.75	0.58	0.50	0.33	0.40	0.22	0.10	1.00	0.51
P(action 1 lag)	0.19	0.57	0.43	0.43	0.46	0.38	0.50	0.83	0.00	0.29	0.00	0.14	0.40	0.40	0.14	0.00	0.00	0.44	0.31
P(action 2 lag)	0.06	0.00	0.00	0.43	0.00	0.13	0.00	0.00	0.67	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.09
P(action 3 lag)	0.75	0.43	0.57	0.14	0.46	0.50	0.50	0.00	0.33	0.71	0.00	0.86	0.50	0.60	0.71	0.67	0.67	0.56	0.50
P(action 4 lag)	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.10	0.00	0.14	0.00	0.33	0.00	0.05

Therefore, the average probability of "changing lane immediately" by individuals is 0.49 and the average probability of "wait for an acceptable gap" is 0.51, which appear almost the same. However, in the lag vehicle role about the drivers keep their current speed on average half the time, 31% of the time they yield for target vehicle, 9% of the time they accelerate to close the gap and only 5% of the time do they change lanes in response to another vehicle's lane change.

The lead vehicle actions cannot be considered as the actions of the subjects because the actions of the front vehicles of the subjects were collected as lead vehicle actions. Therefore, each single action of lead vehicle is done by a single individual who were not the study's subjects.

3.4.4.3 Comparison of Target Vehicle Actions (RP)

Table 3-14 shows the results for the target vehicle action of change lane. The test fails to reject the null hypothesis; therefore, the distribution of the change lane appears similar for all four cases. The sample size likely impacts this outcome because the proportion of the "change lane" action appears different for the congested/merging case and the p-value indicates a significant difference exists at a seven percent level of significance. Since the target vehicle can take only two actions, the same results occur for "do not change lane and wait for another acceptable gap." The target vehicle usually waits for an acceptable gap to change lanes during uncongested conditions. The proportion changing lanes reaches 61% for the uncongested/merging case, but the proportion drops to 26% for the congested/merging case. The less decisive outcome indicates the need for dimensional tests on the target vehicle's actions.

Table 3-14. Chi-square test on "Change Lane" Action of Target Vehicle (RP)

Sample	Proportion	Hypothesis Test		
CM	0.26	Chi-square test	Chi-square (Observed value)	7.12
CD	0.44		Chi-square (Critical value)	7.81
UM	0.53		DF	3.00
UD	0.6		p-value	0.06

3.4.4.4 Dimensional Hypothesis Tests on Target Vehicle Actions (RP)

The authors also conduct dimensional tests that investigate the target vehicle actions in congested versus uncongested and merging versus discretionary lane changing situations. The proportional hypothesis test identifies a significant difference (p-value = 0.04) between the congested and uncongested actions of the target vehicle; therefore, the congestion level influences driver behavior. The geometry does not appear to significantly impact target vehicle behavior due to its large p-value (0.78).

3.4.4.5 Comparison of Lead Vehicle Actions (RP)

The study applies the chi-square test to identify any significant differences between the four cases for each action. The fifth action of lead vehicle specified in SP ("Do not care what is happening behind you") cannot be captured in RP, so this action is eliminated in RP data analysis as well as in comparison of SP and RP. Table 3-15 summarizes the results of chi-square test for all actions of a lead vehicle. The sample size likely impacts this outcome because the proportion of the "decelerating" action appear different for the congested and uncongested cases with p-values that indicate a significant difference exists at a seven percent level of significance. The chi-square test indicates that the RP of accelerating, changing lanes and keeping the current speed as a lead vehicle do not depend on the different traffic and geometry situations. The lead vehicle drivers most frequently accelerate to cooperate with the target vehicle during uncongested traffic and maintain speed during congested conditions. The inconclusive results indicate a need to identify significant differences across the geometry and congestion dimensions of the lead vehicle's actions.

Table 3-15. Chi-square test on Actions of Lead Vehicle (RP)

Lead Vehicle: Accelerating (Cooperating)				
Sample	Proportion	Hypothesis Test		
CM	0.17	Chi-square test	Chi-square (Observed value)	7.35
CD	0.14		Chi-square (Critical value)	7.81
UM	0.44		DF	3.00
UD	0.28		p-value	0.21
Lead Vehicle: Decelerating (Closing the Gap)				
Sample	Proportion	Hypothesis Test		
CM	0.17	Chi-square test	Chi-square (Observed value)	6.97
CD	0.10		Chi-square (Critical value)	8.07
UM	0.00		DF	3.00
UD	0.02		p-value	0.07
Lead Vehicle: Keep Current Speed				
Sample	Proportion	Hypothesis Test		
CM	0.6	Chi-square test	Chi-square (Observed value)	4.09
CD	0.69		Chi-square (Critical value)	7.62

UM	0.44		DF	3.00
UD	0.6		p-value	0.6
Lead Vehicle: Changing Lane				
Sample	Proportion	Hypothesis Test		
CM	0.08	Chi-square test	Chi-square (Observed value)	0.66
CD	0.069		Chi-square (Critical value)	7.45
UM	0.11		DF	3.00
UD	0.11		p-value	0.95

3.4.4.6 Dimensional Hypothesis Tests on Lead Vehicle Actions (RP)

Table 3-16 (includes p-values of z-tests) summarizes the dimensional hypothesis tests across the geometry and congestion dimensions. The proportion of the "accelerating" and "decelerating" actions appear partially significant different for the congested and uncongested cases while congestion plays no role in the changing lane and maintain speed actions. Geometry appears insignificant for all lead vehicle actions. The sample size may affect this result.

Table 3-16. Summary of Dimensional Hypothesis Tests on Lead Vehicle (RP) Actions

Lead Vehicle	Congested vs Uncongested	Merging vs Discretionary
Option 1	0.08	0.83
Option 2	0.09	0.73
Option 3	0.53	0.53
Option 4	0.77	1.00

3.4.4.7 Comparison of Lag Vehicle Actions (RP)

The study applies the chi-square test to identify any significant differences between the four cases for each action. Table 3-17 summarizes the results of chi-square test for all actions of a lag vehicle. The hypothesis tests indicate that lag vehicle's actions appear similar for accelerate and change lanes, but a significant difference exists between the cases for the decelerate and maintain speed actions. The lag vehicle drivers most frequently decelerate to cooperate with the target vehicle during congested conditions and maintain speed during uncongested conditions.

Table 3-17. Chi-square test on Actions of Lag Vehicle (RP)

Lag Vehicle: Decelerating (Cooperating)				
Sample	Proportion	Hypothesis Test		
CM	0.52	Chi-square test	Chi-square (Observed value)	11.19
CD	0.65		Chi-square (Critical value)	7.96
UM	0.31		DF	3.00
UD	0.26		p-value	0.00
Lag Vehicle: Accelerating (Closing the Gap)				
Sample	Proportion	Hypothesis Test		
CM	0.10	Chi-square test	Chi-square (Observed value)	5.01
CD	0.15		Chi-square (Critical value)	7.32
UM	0.00		DF	3.00
UD	0.03		p-value	0.11
Lag Vehicle: Keep Current Speed				
Sample	Proportion	Hypothesis Test		
CM	0.38	Chi-square test	Chi-square (Observed value)	15.21
CD	0.19		Chi-square (Critical value)	7.62
UM	0.62		DF	3.00
UD	0.66		p-value	<0.0001
Lag Vehicle: Changing Lane				
Sample	Proportion	Hypothesis Test		
CM	0.00	Chi-square test	Chi-square (Observed value)	3.04
CD	0.00		Chi-square (Critical value)	8.57
UM	0.08		DF	3.00
UD	0.05		p-value	0.37

3.4.4.8 Dimensional Hypothesis Tests on Lag Vehicle Actions (RP)

The dimensional hypothesis tests shown in Table 3-18 reveal that congestion affects the lag vehicle's deceleration, acceleration, maintain speed actions and changing lanes significantly or partially significant. Roadway geometry does not significantly affect lag vehicle actions.

Table 3-18. Summary of Dimensional Hypothesis Tests on Lag Vehicle (RP) Actions

Lag Vehicle	Congested vs Uncongested	Merging vs Discretionary
Option 1	<0.0001	0.53
Option 2	0.1	1.00
Option 3	<0.0001	0.83
Option 4	0.09	0.96

3.4.5 Discussion about Lane Changing Players' Actions in Different Situations

The overall results show that the congestion plays a significant role in driver actions in the target, lag and lead vehicle roles, which disagrees with the SP findings. The geometry does not impact the behaviors of the drivers of the target, lead and lag vehicles which appears consistent with the SP outcomes. Therefore, driver behavior appears impacted by congestion rather than geometry, and SP data collection may pose a concern for driver behavior analysis.

3.4.6 Analysis of Action of Vehicles Involved in Lane Changing Execution (RP)

This section investigates the actions of each driver involved in lane changing execution to identify any significant differences in the probabilities of the actions of the target, lead and lag vehicles roles.

3.4.6.1 Analysis of Target Vehicle Actions (RP)

The chi-square test seeks to identify any significant differences between the proportion of target vehicle's actions for each geometric and traffic case. The test interpretation is:

H_0: The proportions are equal.

H_a: At least one proportion is different from another.

Based on the chi-square test and Chi-Square hypothesis test output shown in Table 3-19, three cases (UD and CD) may have similar proportions of "change lane" and "do not change lane" actions. The congested/merging and uncongested/merging cases have a significant difference between the two actions because a majority of drivers (74% and 61% respectively) "do not change lane" and wait for an acceptable gap.

Table 3-19. Hypothesis Tests' Results of Target Vehicle's Actions in Four Lane Changing Situations

	UM	UD	CM	CD
p-value of Chi-square test	0.09	0.53	0.001	0.48

3.4.6.2 Analysis of Lead Vehicle Actions (RP)

The study uses the chi-square test to identify any significant differences between the proportions of the lead vehicle's actions for each geometric and traffic case. The test interpretation is:

H_0: The proportions are equal.

H_a: At least one proportion is different from another.

Based on the hypothesis test output shown in Table 3-20, all four cases (UM,CD, CM and UD) experience a significant or partially significant difference among their lead vehicle action proportions. The observed action of "keep current speed" occurs more frequently (>60%) than the other actions for the CD, CM and UD cases.

Table 3-20. Hypothesis Tests' Results of Lead Vehicle's Actions in Four Lane Changing Situations

	UM	UD	CM	CD
p-value of Chi-square test	0.06	< 0.0001	0.02	< 0.0001

3.4.6.3 Analysis of Lag Vehicle Actions (RP)

The study uses the chi-square test to identify any significant differences between the proportions of the lag vehicle's actions for each geometric and traffic case. The test interpretation is:

H_0: The proportions are equal.

H_a: At least one proportion is different from another.

Based on the hypothesis test output shown in Table 3-21, a significant difference exists between the lag vehicle's actions in all cases. The drivers most frequently (> 50%) decelerate in congested conditions and maintain current speed (> 60%) during uncongested situations; these frequently occurring actions represent the main significant differences in the frequency of lag vehicle's actions.

Table 3-21. Hypothesis Tests' Results of Lag Vehicle's Actions in Four Lane Changing Situations

	UM	UD	CM	CD
p-value of Chi-square test	<0.0001	< 0.0001	0.000	< 0.0001

3.4.7 Discussion on SP and RP

Previously, Knoop et al. (2018) conducted an online survey to investigate the strategy that drivers choose at the lane changing moment; however, their study did not compare their results with RP observations to confirm its validity. This research compares the stated preference and revealed preference of lane changing behaviors to validate the suitability of stated preference data as a substitute for revealed preference data when studying lane changing and calibrating lane changing models.

In this study, the researchers conducted online surveys and naturalistic driving experiments to understand the SP and RP of drivers' lane changing behaviors. After conducting all analyses, the roadway geometry situations does not appear to impact the behaviors of the target, lead and lag vehicles for both the SP and RP data. However, the congestion levels appear to impact many of the naturalistic target, lead and lag vehicle actions, which remains inconsistent with the SP outcomes where congestion did not impact behavior. The distribution of chosen actions appears different in the online surveys and naturalistic driving. Figure 3-7 shows the distribution of the target, lead and lag vehicles' actions in all four situations based on stated preference and revealed preference data collection.

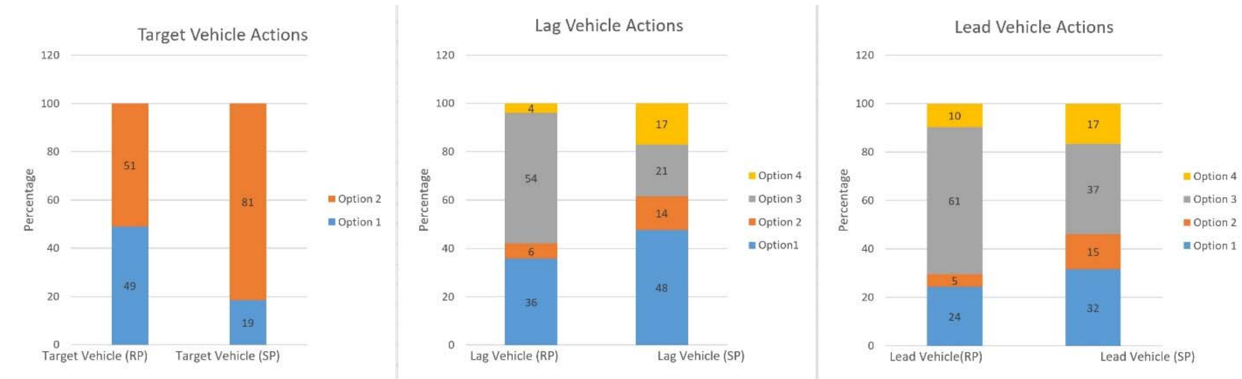


Figure 3-7. Distribution of Target, Lead and Lag vehicles' Actions

3.4.7.1 Hypothesis Tests Between RP and SP of Lane Changing Behavior Players Actions

The author conducts the chi-square tests between the RP and SP data to test for significant differences by each role (target, lead and lag).The test interpretation is as follows:

H0: The proportions are equal.

Ha: At least one proportion is different from another.

The results indicated that there is a significant difference between the actions of target, lead and lag vehicles in RP and SP data sets (p-value<0.0001 in all three cases). Table 3-22 summarizes the results of chi-square tests of different roles.

Table 3-22:Summary of k proportions test for comparison of RP and SP

Summary of k proportions test			
Chi-square test	Target vehicle	Lead vehicle	Lag vehicle
Chi-square (Observed value)	180.35	169.37	221.72
Chi-square (Critical value)	7.81	14.07	14.07
DF	3	7	7
p-value	< 0.0001	< 0.0001	< 0.0001
alpha	0.05	0.05	0.05

Afterwards, the ad-hoc test is conducted to investigate which actions of RP and SP in each role are in the same group which means no significant differences exist between the frequencies of proportions of these actions. Tables 3-23 to 3-25 show the results of the ad-hoc test for target, lead and lag vehicles respectively. The actions which are shown with the same alphabetic letters such as "A", "B" and etc. are in the same group and no significant differences exist between their frequencies or proportions. As an example, actions 1 and 2 of the target vehicle in RP data set are in the same group (no significant difference between their proportions). They were shown with "B" letter. However, action 1 and action 2 of target vehicle in SP data set, are in different groups (A and C), which means not only their proportions are significantly different from each other, but also the frequencies (proportions) of each of these actions are significantly different from the target vehicle's actions in RP data set.

Table 3-23:Summary of ad-hoc test for target vehicle

Sample	Proportion	Groups		
Target, Act1-SP	0.185	A		
Target, Act1-RP	0.488		B	
Target, Act2-RP	0.512		B	
Target, Act2-SP	0.815			C

Table 3-24:Summary of ad-hoc test for lead vehicle

Sample	Proportion	Groups			
Lead, Act2-RP	0.052	A			
Lead, Act4-RP	0.096	A	B		
Lead, Act2-SP	0.146	A	B		
Lead, Act4-SP	0.165	A	B		
Lead, Act1-RP	0.243		B	C	
Lead, Act1-SP	0.315			C	
Lead, Act3-SP	0.373			C	
Lead, Act3-RP	0.609				D

Table 3-25:Summary of ad-hoc test for lag vehicle

Sample	Proportion	Groups				
Lag, Act4-RP	0.040	A				
Lag, Act2-RP	0.063	A	B			
Lag, Act2-SP	0.138	A	B	C		
Lag, Act4-SP	0.171		B	C		
Lag, Act3-SP	0.215			C	D	
Lag, Act1-RP	0.357				D	E
Lag, Act1-SP	0.476					E
Lag, Act3-RP	0.540					E

3.4.8 Power analysis

In this section, the author attempts to show the required sample size of real-world behavior observation such that a specific percentage of the times have a significant difference with 95% confidence level between the RP proportion (expected proportion) and SP proportion of the critical action of each role (target, lead and lag vehicles). The critical action for each role is identified by calculating the 95% confidence interval for each action of each role. The largest confidence interval among the actions of each role, specifies the most critical action. Table 3-26 shows the results of calculated confidence intervals for each action. Based on these results either waiting for an acceptable gap o changing lane immediately (here waiting for an acceptable gap is chosen), keeping current speed and decelerating to cooperate with target vehicle are the most critical actions of target, lead and lag vehicles respectively. Appendix H shows a sample of calculation (for lag vehicle) for obtaining the confidence intervals to determine critical actions of each role.

Table 3-26: Confidence intervals of vehicles' actions

Vehicles' Actions	95% Confidence Interval	Interval distance
Target vehicle (changing lane immediately)	(0.14, 0.24)	0.1
Target vehicle (waiting for an acceptable gap)	(0.76, 0.86)	0.1
Lag vehicle (decelerating)	(0.42, 0.54)	0.12
Lag vehicle (accelerating)	(0.1, 0.18)	0.08
Lag vehicle (keeping current speed)	(0.16, 0.26)	0.1
Lag vehicle (changing lane)	(0.13, 0.21)	0.07
Lead vehicle (accelerating)	(0.26, 0.37)	0.11
Lead vehicle (decelerating)	(0.1, 0.19)	0.09
Lead vehicle (keeping current speed)	(0.31, 0.43)	0.12
Lead vehicle (changing lane)	(0.12, 0.21)	0.09

Afterwards, the graph of number of sample size-power value for each role is plotted based on 0.05 as significance level, the expected proportion which is RP proportions of critical actions of each role (0.51 for target, 0.61 for lead and 0.36 for lag vehicles) and the existing SP proportion (0.81 for target, 0.37 for lead and 0.48 for lag vehicles). Figures 3-8 to 3-10 show the sample size-power value graphs of target, lead and lag vehicles respectively. For instance, for 90% of the times that have a significant difference between the RP and SP proportions of lag vehicle actions with 95% confidence level, the required sample size of lag vehicle's actions is 174. The same interpretation can be conducted for lead and lag vehicles actions.

The expected proportion is assumed to be RP proportion of critical action of each role and the significance level is 0.05. The test interpretation is as follows:

H0: The difference between the proportions is equal to 0.
Ha: The difference between the proportions is different from 0.

The results indicate that:

- For the target vehicle, for the given parameters, for an alpha of 0.05, the necessary sample size to reach a power of 0.9 is 24 observations.
- For the lead vehicle, for the given parameters, for an alpha of 0.05, the necessary sample size to reach a power of 0.9 is 43 observations.
- For the lag vehicle, for the given parameters, for an alpha of 0.05, the necessary sample size to reach a power of 0.9 is 174 observations.

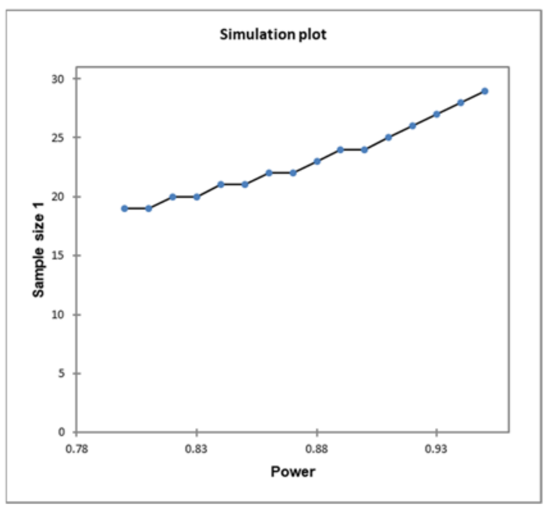


Figure 3-8:Sample size versus power value for target vehicle's observation

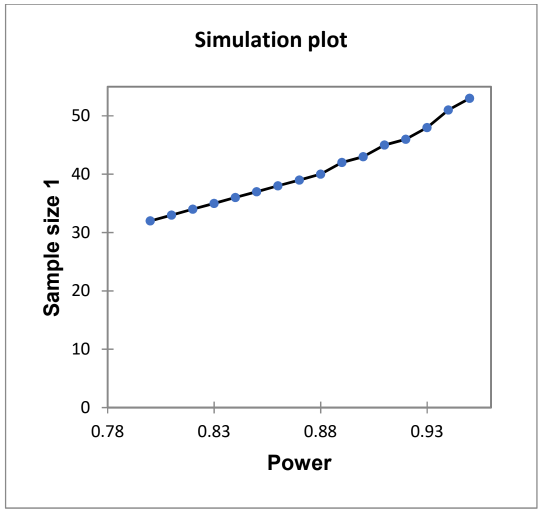


Figure 3-9:Sample size versus power value for lead vehicle's observation

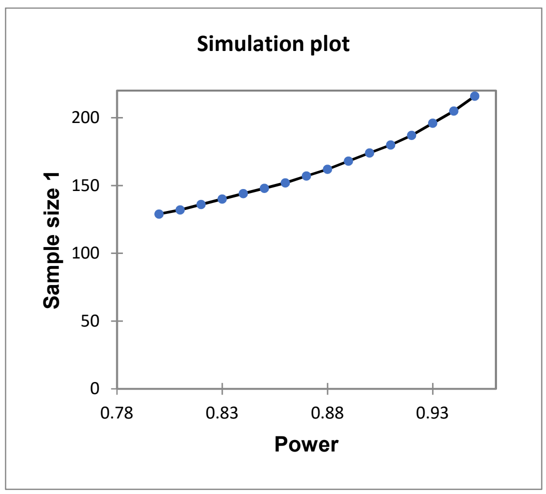


Figure 3-10:Sample size versus power value for lag vehicle's observation

3.5 Conclusion

This study aims to understand the potential actions of target, lead and lag vehicle which are introduced as the main vehicles involved in a lane changing process. The paper's main contribution is determining the driver actions to be used in developing lane changing models, especially the ones which consider the interactions of drivers such game theoretical models. This paper investigates both the SP and RP of lane changing behaviors in four different traffic and geometry situations (UM, UC, CM, CD) and compare the naturalistic driving behavior with the stated preferences in online surveys. In the first phase, the authors conduct mixed methodological approach; focus groups and online surveys to obtain the stated preference of people as target, lead and lag vehicles in lane changing situations. The second phase collects naturalistic driving behavior of lane changing using video recordings. Each driver might automatically be placed as target vehicle or lag vehicle which their actions were collected by analyzing the speed changes. The actions of the front vehicle (accelerating, decelerating, keeping current speed and changing lane) were also recorded as the lead vehicle.

After all statistical analysis, the results show that the four combinations of geometry and congestion level do not impact the actions of the target and lead vehicles in the SP data, but the congestion impacts the actions of target, lead and lag vehicles in the RP data. Based on the RP indications, as a target vehicle, people change lane immediately more often in uncongested situations, and more aggressively than expected. The drivers as the lead vehicle seem to accelerate to cooperate with target vehicle much more in uncongested situations. Drivers as the lag vehicle decelerate to cooperate more often with the target vehicle in congested situations, but they keep their current speed in uncongested situations. As lead vehicle, people mostly keep their current speed in congested situation, but they either accelerate to cooperate and keep their current speed in uncongested situations. Moreover, the geometry does not affect the naturalistic behavior of drivers in the target, lead and lag vehicle roles. This study also compares the stated preference and revealed preference data sets. Overall, the SP data fails to capture the real-world behaviors of lane changing actions; therefore, naturalistic driving behavior must be used for lane changing model calibration and assessing the expectations of drivers for autonomous vehicle actions during lane changing.

Based on SP and RP result the most frequent actions of lag and lead vehicles are:

Lag Vehicle: (Decelerate to cooperate with the target vehicle and Keep current speed)

Lead Vehicle: (Accelerate to cooperate with the target vehicle and Keep current speed)

The outcomes of this study is applicable to be used as a foundation for developing lane changing models which consider the interactions of drivers in lane changing process. Additionally, the results of the study can be applied to traffic simulation software for simulating lane changing behaviors.

The main limit of this research includes the number of subjects which their naturalistic driving behavior were collected. Due to safety concerns of University of Texas at Arlington Institutional Review Board, the researcher was limited to a certain number of subjects. Moreover, if the time and distance of observation increases, the behavior of people can be captured more and the reliability of results increases, but the researcher had to consider a specific time and distance that subjects would not face dangerous situations. Another limit includes the lack of instruments for capturing naturalistic driving behavior data such installing multiple cameras all around the vehicle to be able to record the traffic situation as well as and all movements of vehicles involved in lane changing process.

This research can be strengthened by collecting a large sample of real-world lane changing behaviors. A larger sample would improve the understanding of the real actions of drivers. Furthermore, the revealed preferences can be obtained via vehicles' trajectory data such as NGSIM data set and then compared to stated preferences. The comprehensive naturalistic driving behavior data such as SHRP2 data sets are also can be used for such studies. The data which are used for the purpose of this study should be able to capture the instantaneous actions of vehicles involved in lane changing process target, lead and lag vehicles). The acceleration, deceleration, keeping current speed and changing lane of lead and lag vehicle as well as target vehicle' actions (changing lane immediately and waiting for an acceptable gap) should has to be observed by the potential real-world data.

3.6 References

Agrawal, A.W., Dill, J., Nixon, H., 2010. Green transportation taxes and fees: A survey of public preferences in California. Transp. Res. Part Transp. Environ. 15, 189–196. https://doi.org/10.1016/j.trd.2009.11.003

Ahern, A.A., Tapley, N., 2008. The use of stated preference techniques to model modal choices on interurban trips in Ireland. Transp. Res. Part Policy Pract. 42, 15–27. https://doi.org/10.1016/j.tra.2007.06.005

Anand, S., Padmanabham, P., Govardhan, A., 2014. Application of Factor Analysis to k-means Clustering Algorithm on Transportation Data. https://doi.org/10.5120/16673-6677

Bajari, P., Hong, H., Ryan, S.P., 2010. Identification and Estimation of a Discrete Game of Complete Information. Econometrica 78, 1529–1568. https://doi.org/10.3982/ECTA5434

Balal, E., Cheu, R.L., Sarkodie-Gyan, T., 2016. A binary decision model for discretionary lane changing move based on fuzzy inference system. Transp. Res. Part C Emerg. Technol. 67, 47–61. https://doi.org/10.1016/j.trc.2016.02.009

Ben-Akiva, M.E., Choudhury, C., Toledo, T., 2006. Lane changing models, in: Proceedings of the International Symposium of Transport Simulation.

Bertram, D., n.d. Likert Scale \lick-urt\, n. 11.

Björklund, G.M., Åberg, L., 2005. Driver behaviour in intersections: Formal and informal traffic rules. Transp. Res. Part F Traffic Psychol. Behav. 8, 239–253. https://doi.org/10.1016/j.trf.2005.04.006

Bryant, F.B., Yarnold, P.R., Michelson, E.A., 1999. Statistical Methodology. Acad. Emerg. Med. 6, 54–66. https://doi.org/10.1111/j.1553-2712.1999.tb00096.x

Cao, X., Young, W., Sarvi, M., 2013. Exploring Duration of Lane Change Execution 17.

Choudhury, C., Ben-Akiva, M.E., Toledo, T., Rao, A., Lee, G., 2007. State dependence in lane changing models. Elsevier.

Clifton, K.J., Handy, S.L., 2003. Qualitative Methods in Travel Behaviour Research, in: Transport Survey Quality and Innovation. Emerald Group Publishing Limited, pp. 283–302. https://doi.org/10.1108/9781786359551-016

Coifman, B., Cassidy, M., 2002. Vehicle reidentification and travel time measurement on congested freeways. Transp. Res. Part Policy Pract. 36, 899–917. https://doi.org/10.1016/S0965-8564(01)00046-5

Collins, A., Rose, J., Hess, S., 2007. Stated Preference survey design in air travel choice behaviour modelling. Proc. Eur. Transp. Conf. 2007 HELD 17-19 Oct. 2007 LEIDEN Neth.

Dill, J., Voros, K., 2007. Factors Affecting Bicycling Demand: Initial Survey Findings from the Portland, Oregon, Region. Transp. Res. Rec. J. Transp. Res. Board 2031, 9–17. https://doi.org/10.3141/2031-02

Dula, C.S., Geller, E.S., 2003. Risky, aggressive, or emotional driving: Addressing the need for consistent communication in research. J. Safety Res. 34, 559–566. https://doi.org/10.1016/j.jsr.2003.03.004

Errampalli, M., Okushima, M., Akiyama, T., n.d. Lane Change Modelling with Fuzzy Logic in Microscopic Traffic Simulation 6.

Flamm, B.J., Agrawal, A.W., 2012. Constraints to green vehicle ownership: A focus group study. Transp. Res. Part Transp. Environ. 17, 108–115. https://doi.org/10.1016/j.trd.2011.09.013

Fletcher, C.N., Garasky, S.B., Jensen, H.H., Nielsen, R.B., 2010. Transportation Access: A Key Employment Barrier for Rural Low-Income Families. J. Poverty 14, 123–144. https://doi.org/10.1080/10875541003711581

Gan, H., Ye, X., 2012. Urban freeway user' diversion response to variable message sign displaying the travel time of both freeway and local street. IET Intell. Transp. Syst. 6, 78–86. https://doi.org/10.1049/iet-its.2011.0070

Gipps, P.G., 1986. A model for the structure of lane-changing decisions. Transp. Res. Part B Methodol. 20, 403–414. https://doi.org/10.1016/0191-2615(86)90012-3

Glasgow, N., Blakely, R.M., 2000. Older Nonmetropolitan Residents' Evaluations of Their Transportation Arrangements. J. Appl. Gerontol. 19, 95–116. https://doi.org/10.1177/073346480001900106

Golob, T.F., Regan, A.C., 2001. Impacts of highway congestion on freight operations: perceptions of trucking industry managers. Transp. Res. Part Policy Pract. 35, 577–599. https://doi.org/10.1016/S0965-8564(00)00008-2

Greenwood, M., Kendrick, T., Davies, H., Gill, F.J., 2017. Hearing voices: Comparing two methods for analysis of focus group data. Appl. Nurs. Res. ANR 35, 90–93. https://doi.org/10.1016/j.apnr.2017.02.024

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2014. Multivariate data analysis.

Hayley, A.C., Ridder, B. de, Stough, C., Ford, T.C., Downey, L.A., 2017. Emotional intelligence and risky driving behaviour in adults. Transp. Res. Part F Traffic Psychol. Behav. 49, 124–131. https://doi.org/10.1016/j.trf.2017.06.009

Hidas, P., 2005. Modelling vehicle interactions in microscopic simulation of merging and weaving. Transp. Res. Part C Emerg. Technol. 13, 37–62. https://doi.org/10.1016/j.trc.2004.12.003

Hidas, P., 2002. Modelling lane changing and merging in microscopic traffic simulation. Transp. Res. Part C Emerg. Technol. 10, 351–371. https://doi.org/10.1016/S0968-090X(02)00026-8

Huth, V., Füssl, E., Risser, R., 2014. Motorcycle riders' perceptions, attitudes and strategies: Findings from a focus group study. Transp. Res. Part F Traffic Psychol. Behav. 25, 74–85. https://doi.org/10.1016/j.trf.2014.05.004

k proportions test [WWW Document], n.d. . Xlstat Your Data Anal. Solut. URL https://www.xlstat.com/en/solutions/features/comparison-of-k-proportions (accessed 2.24.19).

Kesting, A., Treiber, M., Helbing, D., 2007. General Lane-Changing Model MOBIL for Car-Following Models. Transp. Res. Rec. J. Transp. Res. Board 1999, 86–94. https://doi.org/10.3141/1999-10

Keyvan-Ekbatani, M., Knoop, V.L., Daamen, W., 2016a. Categorization of the lane change decision process on freeways. Transp. Res. Part C Emerg. Technol. 69, 515–526. https://doi.org/10.1016/j.trc.2015.11.012

Keyvan-Ekbatani, M., Knoop, V.L., Daamen, W., 2016b. Categorization of the lane change decision process on freeways. Transp. Res. Part C Emerg. Technol. 69, 515–526. https://doi.org/10.1016/j.trc.2015.11.012

Kita, H., 1999. A merging–giveway interaction model of cars in a merging section: a game theoretic analysis. Transp. Res. Part Policy Pract. 33, 305–312. https://doi.org/10.1016/S0965-8564(98)00039-1

Knight, W., n.d. Why Cars Won't be Driverless Anytime Soon [WWW Document]. MIT Technol. Rev. URL https://www.technologyreview.com/s/513531/proceed-with-caution-toward-the-self-driving-car/ (accessed 9.23.18).

Knoop, V.L., Keyvan-Ekbatani, M., de Baat, M., Taale, H., Hoogendoorn, S.P., 2018. Lane Change Behavior on Freeways: An Online Survey Using Video Clips [WWW Document]. J. Adv. Transp. https://doi.org/10.1155/2018/9236028

Kondyli, A., Elefteriadou, L., 2011. Modeling Driver Behavior at Freeway-Ramp Merges. Transp. Res. Rec. J. Transp. Res. Board 2249, 29–37. https://doi.org/10.3141/2249-05

Kondyli, A., Elefteriadou, L., 2009. Driver Behavior at Freeway-Ramp Merging Areas. Transp. Res. Rec. J. Transp. Res. Board 2124, 157–166. https://doi.org/10.3141/2124-15

Kusuma, A., Liu, R., Choudhury, C., Montgomery, F., 2015. Lane-Changing Characteristics at Weaving Section. Presented at the Transportation Research Board 94th Annual MeetingTransportation Research Board.

Lei, P.-W., Wu, Q., 2007. Introduction to Structural Equation Modeling: Issues and Practical Considerations. Educ. Meas. Issues Pract. 26, 33–43. https://doi.org/10.1111/j.1745-3992.2007.00099.x

Li Gen, Sun Lu, Pan Yiyong, Yu Ye, n.d. Analysis of Merging Behavior Parameters Using NGSIM Data Sets. CICTP 2016, Proceedings. https://doi.org/10.1061/9780784479896.008

Li, Z., Hensher, D.A., 2012. Congestion charging and car use: A review of stated preference and opinion studies and market monitoring evidence. Transp. Policy, URBAN TRANSPORT INITIATIVES 20, 47–61. https://doi.org/10.1016/j.tranpol.2011.12.004

Liu, H., Xin, W., Adam, Z., Ban, X.J., 2007. A game theoretical approach for modelling merging and yielding behaviour at freeway on-ramp sections, in: 17th International Symposium on Transportation and Traffic Theory, London, UK.

Loo, B.P.Y., 2002. Role of Stated Preference Methods in Planning for Sustainable Urban Transportation: State of Practice and Future Prospects. J. Urban Plan. Dev. 128, 210–224. https://doi.org/10.1061/(ASCE)0733-9488(2002)128:4(210)

Machado-León, J.L., de Oña, J., de Oña, R., Eboli, L., Mazzulla, G., 2016. Socio-economic and driving experience factors affecting drivers' perceptions of traffic crash risk. Transp. Res. Part F Traffic Psychol. Behav. 37, 41–51. https://doi.org/10.1016/j.trf.2015.11.010

Marczak, F., Daamen, W., Buisson, C., 2013. Merging behaviour: Empirical comparison between two sites and new theory development. Transp. Res. Part C Emerg. Technol. 36, 530–546. https://doi.org/10.1016/j.trc.2013.07.007

Moridpour, S., Sarvi, M., Rose, G., 2013. Lane changing models: a critical review. Transp. Lett.

Ortúzar, J. de D., Iacobelli, A., Valeze, C., 2000. Estimating demand for a cycle-way network. Transp. Res. Part Policy Pract. 34, 353–373. https://doi.org/10.1016/S0965-8564(99)00040-3

Peeta, S., Ramos, J.L., 2006. Driver response to variable message signs-based traffic information. IEE Proc. - Intell. Transp. Syst. 153, 2. https://doi.org/10.1049/ip-its:20055012

Peeta, S., Zhang, P., Zhou, W., 2005. Behavior-based analysis of freeway car–truck interactions and related mitigation strategies. Transp. Res. Part B Methodol. 39, 417–451. https://doi.org/10.1016/j.trb.2004.06.002

Peng, J., Guo, Y., Fu, R., Yuan, W., Wang, C., 2015. Multi-parameter prediction of drivers' lane-changing behaviour with neural network model. Appl. Ergon. 50, 207–217. https://doi.org/10.1016/j.apergo.2015.03.017

Rahman, M., Chowdhury, M., Xie, Y., He, Y., 2013. Review of Microscopic Lane-Changing Models and Future Research Opportunities. IEEE Trans. Intell. Transp. Syst. 14, 1942–1956. https://doi.org/10.1109/TITS.2013.2272074

Rayle, L., Dai, D., Chan, N., Cervero, R., Shaheen, S., 2016. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transp. Policy 45, 168–178. https://doi.org/10.1016/j.tranpol.2015.10.004

Razo, M., Gao, S., 2013. A rank-dependent expected utility model for strategic route choice with stated preference data. Transp. Res. Part C Emerg. Technol., Selected papers from the Seventh Triennial Symposium on Transportation Analysis (TRISTAN VII) 27, 117–130. https://doi.org/10.1016/j.trc.2011.08.009

Razo, M., Gao, S., 2010. Strategic Thinking and Risk Attitudes in Route Choice. Transp. Res. Rec. J. Transp. Res. Board 2156, 28–35. https://doi.org/10.3141/2156-04

Salvucci, D.D., n.d. Inferring Driver Intent: A Case Study in Lane-Change Detection. Th Annu. Meet. 4.

Sarvi, M., Kuwahara, M., 2007. Microsimulation of Freeway Ramp Merging Processes Under Congested Traffic Conditions. IEEE Trans. Intell. Transp. Syst. 8, 470–479. https://doi.org/10.1109/TITS.2007.895305

Schakel, W., Knoop, V., van Arem, B., 2012. Integrated Lane Change Model with Relaxation and Synchronization. Transp. Res. Rec. J. Transp. Res. Board 2316, 47–57. https://doi.org/10.3141/2316-06

Stathopoulos, A., Valeri, E., Marcucci, E., 2012. Stakeholder reactions to urban freight policy innovation. J. Transp. Geogr., Special Section on Rail Transit Systems and High Speed Rail 22, 34–45. https://doi.org/10.1016/j.jtrangeo.2011.11.017

Stinson, M., Bhat, C., 2003. Commuter Bicyclist Route Choice: Analysis Using a Stated Preference Survey. Transp. Res. Rec. J. Transp. Res. Board 1828, 107–115. https://doi.org/10.3141/1828-13

Sun, Daniel(Jian), Elefteriadou, L., 2011. Lane-changing behavior on urban streets: A focus group-based study. Appl. Ergon. 42, 682–691. https://doi.org/10.1016/j.apergo.2010.11.001

Sun, Daniel, Elefteriadou, L., 2011. Information Categorization Based on Driver Behavior for Urban Lane-Changing Maneuvers. Transp. Res. Rec. J. Transp. Res. Board 2249, 89–94. https://doi.org/10.3141/2249-11

Sun, D., Elefteriadou, L., 2010. Research and Implementation of Lane-Changing Model Based on Driver Behavior. Transp. Res. Rec. J. Transp. Res. Board 2161, 1–10. https://doi.org/10.3141/2161-01

Sun, D. (Jian), Kondyli, A., 2010. Modeling Vehicle Interactions during Lane-Changing Behavior on Arterial Streets. Comput.-Aided Civ. Infrastruct. Eng. 25, 557–571. https://doi.org/10.1111/j.1467-8667.2010.00679.x

Sun, D.J., 2009. A lane-changing model for urban arterial streets (Ph.D.). University of Florida, United States -- Florida.

Svenson, A.L., Gawron, V.J., Brown, T., n.d. General Dynamics.

Talebpour, A., Mahmassani, H.S., Hamdar, S.H., 2015a. Modeling lane-changing behavior in a connected environment: A game theory approach. Transp. Res. Part C Emerg. Technol., Special Issue on International Symposium on Transportation and Traffic Theory 59, 216–232. https://doi.org/10.1016/j.trc.2015.07.007

Talebpour, A., Mahmassani, H.S., Hamdar, S.H., 2015b. Modeling lane-changing behavior in a connected environment: A game theory approach. Transp. Res. Procedia 7, 420–440.

Tashakkori, A., Teddlie, C., Teddlie, C.B., 2003. Handbook of Mixed Methods in Social & Behavioral Research. SAGE.

Toledo, T., Koutsopoulos, H.N., Ben-Akiva, M.E., 2003. Modeling Integrated Lane-Changing Behavior. Transp. Res. Rec. J. Transp. Res. Board 1857, 30–38. https://doi.org/10.3141/1857-04

Wagh, S.T., Razvi, N.A., 2016. Marascuilo Method of Multiple Comparisons (An Analytical Study of Caesarean Section Delivery) 3, 4.

Wang, M., Hoogendoorn, S.P., Daamen, W., van Arem, B., Happee, R., 2015. Game theoretic approach for predictive lane-changing and car-following control. Transp. Res. Part C Emerg. Technol. 58, Part A, 73–92. https://doi.org/10.1016/j.trc.2015.07.009

Wardman, M., 1988. A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour. J. Transp. Econ. Policy 22, 71–91.

Washbrook, K., Haider, W., Jaccard, M., 2006. Estimating commuter mode choice: A discrete choice analysis of the impact of road pricing and parking charges. Transportation 33, 621–639. https://doi.org/10.1007/s11116-005-5711-x

Yao, S., 2015. Game theoretical approach on vehicle-cyclist interaction analysis.

Yim, Y., Khattak, A., Raw, J., 2002. Traveler Response to New Dynamic Information Sources: Analyzing Corridor and Areawide Behavioral Surveys. Transp. Res. Rec. J. Transp. Res. Board 1803, 66–75. https://doi.org/10.3141/1803-10

Zhang, Z., n.d. Analysis of the Traffic Behavior Based on Game Theory, in: International Conference on Transportation Engineering 2009. American Society of Civil Engineers, pp. 501–506.

Chapter 4

Modeling Merging and Discretionary Lane Changing Behaviors Using Game Theoretical Approach

4.1 Introduction

Recently, extensive studies have sought to model driving behaviors. Lane changing represents one of the most challenging driving behaviors to model because it depends on multiple vehicle interactions. Lane changing behavior modeling has been studied vastly, but traffic engineering scholars still attempt to improve the existing models. A more accurate lane changing model would improve traffic simulations and enhance the outcomes of traffic operation projects. The main purpose of this paper is to improve the existing lane changing models using a game theoretical approach.

Since the lane changing maneuver has a noticeable role in causing congestion and collisions, accurate modelling of this behavior has a crucial role in designing traffic simulation tools. Although significant efforts have been made for developing lane changing models during recent decades, most of them do not consider some key parameters such as geometry, weather condition, and broader traffic flow (Rahman et al., 2013). Therefore investigating and developing a more conclusive lane changing model that embraces those parameters represents a meaningful contribution.

Figure 4-1 (Rahman et al., 2013) organizes the different lane changing models that have been investigated in the past decades. Based on this figure, lane changing models are classified in microscopic, macroscopic, and hybrid models. Most of lane changing models are in microscopic level which include four main categories; Incentive Based Model, Artificial Intelligence Model, Discrete Choice Model, and Rule Based Model. The proposed model in this paper is classified as Rule Based Model.

Based on these modeling approaches, lane changing behavior consists of some interactive actions. A driver decides to change lanes based on other drivers' positions and behaviors. The lane changing process does not just depend on only the target vehicle (the one attempting to change lanes), but also on the behavior of the vehicles in the target lane. The lane changing models can become more complex when they consider broader traffic conditions such as lane density *(Choudhury et al, 2007)*.

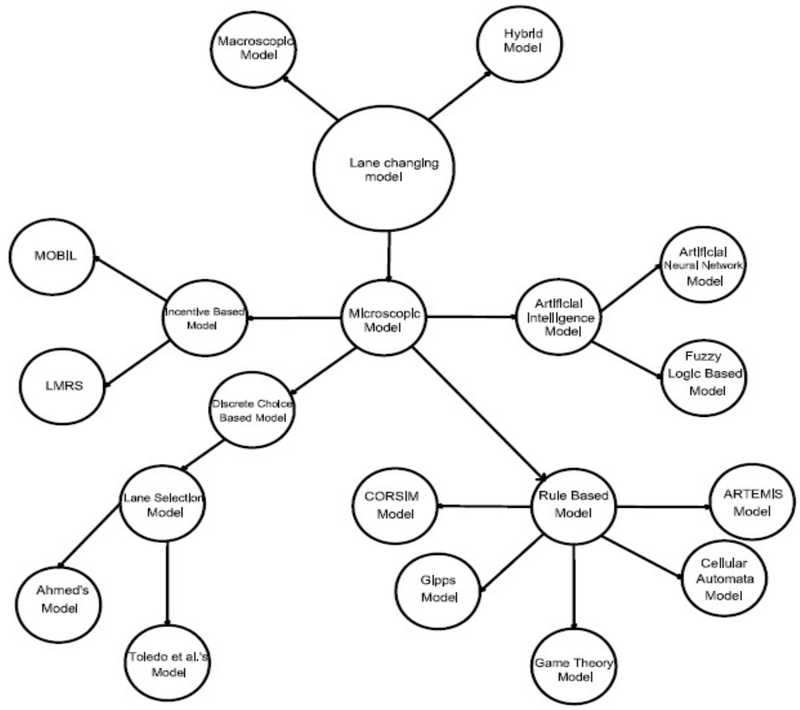


Figure 4-1. "Classification of lane changing models" (Rahman et al. 2013)

Modelling rational traffic behavior requires considering the dynamic interactions between drivers and their sets of actions. Game theory seems appropriate to understand, analyze, and model the sequence of decision making (Talebpour et al., 2015a) because it captures considering the other parties' actions and choices into one's decision making process. Some traffic behaviors contain several traffic participants' decision-making; especially the lane changing behaviors which conflicts between drivers may occur. In order to apply game theory to study lane changing behavior, the type of game (Static/Dynamic, complete/incomplete information, and cooperative/non-cooperative), number of players, set of actions for each player, and their payoff functions should be specified (Kita, 1999).

Overall, modelling lane changing behavior using a game theoretical approach enhances the existing lane changing models by explicit consideration of the logical actions of vehicles involved in the lane changing process. A significant modelling improvement can be implemented in microscopic traffic simulation software to achieve more realistic predictions.

The remainder of this manuscript consists of a literature review, a description of the problem being studied, the game theory model, discussion, and conclusion.

4.2 Literature Review

In the past decades, researchers applied different approaches to model lane changing behaviors. The literature review focuses on two topics. First, the authors review lane changing models with approaches other than game theory. In the second part, the paper investigates lane changing or merging behaviors modeled by a game theoretical approach.

4.2.1 Lane Changing Behavior Models

Gipps (1986) develops a lane changing model in urban areas where traffic signals, heavy vehicles, and other obstructions may affect driving behavior. His model creates a hierarchy of the lane changing process and the actions drivers need to take during the maneuver. *Kesting et al. (2007)*, develop a general model for merging and discretionary lane changing behaviors with the goal of minimizing overall braking induced by lane changes (MOBIL). In their model, the utility of a given lane and also the risk of lane changing have been considered in terms of longitudinal accelerations. This consideration helps to formulate the compact and general safety incentive criteria for symmetric and asymmetric lane changing rules. Their model only represents the last stage of lane changing, which is an operational act; however, it cannot predict the strategic or tactical steps such as vehicle acceleration or deceleration in the lane changing process. *Hidas (2002)* also presents a model of lane changing and merging behaviors, which he names Simulation of Intelligent TRAnsport Systems (SITRAS). SITRAS considers both forced and cooperative lane changing behaviors in traffic congestion situations. Based on his research, a flow-speed relationship can be generated realistically only by forced and cooperative lane changing models. However the SITRAS model only accounts for the immediate leader and follower vehicles and not the broader traffic characteristics such as lane density. The merging behavior is analyzed by (Li Gen et al. 2016) with considering eight parameters that describe the gaps, times to collision between vehicles, and the merging vehicle's speed, which are derived from US Department of Transportation Next Generation Simulation (NGSIM) trajectory data set. Another research by(Schakel et al., 2012) integrate a car-following model with lane changing behavior that represents traffic better at the macroscopic level by considering traffic flow speeds of different lanes, the onset of congestion, and traffic volume of each lane. A driver's binary decision about executing or not executing a discretionary lane changing maneuver using a Fuzzy Inference System (FIS) is developed by*(Balal et al., 2016)* . They consider four variables: "the gap between the subject vehicle and the preceding vehicle in the original lane, the gap between the subject vehicle and the preceding vehicle in the target lane, the gap between the subject vehicle and the following vehicle in the target lane, and the distance between the preceding and following vehicles in the target lanes" to answer "Is it time to begin to move into the target lane?" question.

Some studies investigate the advantages and disadvantages of different lane changing models. For instance, *Moridpour et al. (2013)* explore the existing lane changing models in literature and investigate the strengths and weaknesses of each model. Their classification identifies two main categories of lane changing behavior models (LCBM), driving decision models and driving assistant models. *Ben-Akiva, Choudhury, & Toledo, (2006)* review a series of advanced lane changing models and propose a model with more integrated drivers' behaviors. They also investigate the heterogeneity of the driver population and the correlation between driver's decisions. *Rahman et al. (2013)* reviews and compares lane changing models related to microscopic traffic simulations. They investigate applicable improvements of existing lane changing models.

The literature makes a few comparisons between developed models and micro simulation tools' models. For instance, *Sun & Elefteriadou (2010)* compare their developed model and the lane changing model in CORridor SIMulation (CORSIM). Their study uses driver behavior data to model lane changing behavior. They designed two experiments, a focus group study and an in-vehicle driving test, to collect data associated with lane changing behavior and obtain both lane changing probability and gap acceptance. They test their model in CORSIM and compare it with the embedded lane changing model in CORSIM. They show that their model fits the observed data better than CORSIM's under different traffic congestion levels. However, they only focused on urban arterial areas for lane changing behavior modelling.

During the lane changing maneuver, the current lane changing decision can be affected by an earlier decision making process. *Choudhury et al., (2007)* uses an on-ramp merging model in a congested freeway condition for developing a framework to model state dependency in lane changing behavior. Their proposed model uses state dependency to understand the influences of previous driver decisions on the ongoing decision making process. It also can predict the future decision making situations. However, they just focus on lateral decisions and exclude the longitudinal behaviors of cars for modeling.

Overall, future research must investigate other criteria such as considering traffic congestion downstream in the current lane and target lane because if the driver observes any congestion downstream, then lane changing may not happen. This paper investigates adding this criterion to modeling approaches. The following section reviews, the lane changing models developed with game theory.

4.2.2 Game Theoretical Approach in Traffic Behavior

Recently, some research has explored lane changing modelling using game theoretical approaches. *Zhang, (2009)* presents an analysis of traffic behavior based on game theory because the traffic behaviors represent the outcome of a traffic participant's decision making process and many types of conflicts and interactions between vehicles may occur. (Yao, 2015) also models the interactions of vehicles and bicyclists using a game theoretical approach. The objective of players is to keep current speed while considering safety constraints. A non-cooperative, static, strategic, and with complete information game is used to find Nash equilibrium.

Logically, game theory can model the merging process. *Kita (1999)* models the behavior of merging and through cars using game theory. Both cars try to achieve the maximum benefit by predicting the other's behaviors, which represents a two-person non-zero-sum non-cooperative game; he uses video recording data to model and calibrate the lane changing process. However, he bases the pay-off function for the target and lag vehicles on minimizing the risk of lane changing (according to time to collision), which neglects any speed gaining advantage for the target vehicle. *Liu et al., (2007)*, also develops a vehicle interactions model in a merging situation using a game theory approach. Their game includes the freeway on-coming through vehicle and the on-ramp merging vehicle as players. These vehicles compete with each other to earn the highest revenue during the merging process. The through vehicle tries to maintain its speed and the merging vehicle tries to enter the main lane as soon as possible, which represents a non-cooperative game with adopting strategies from a Nash equilibrium.

Other than general traffic behaviors and the merging process, lane changing can be modeled by game theory. *Talebpour et al. (2015)* propose a lane changing model with a game theoretical approach. They model merging and discretionary lane changing behaviors in one framework. Their model for discretionary lane changing evaluates the lane changing benefits based on acceleration to prevent collision and also the speed gain after the maneuver. In this research, the lag vehicle also investigates whether to cooperate with the target vehicle or not. This model also investigates lane changing behavior in a connected vehicle environment. *Wang et al. (2015)* also propose a lane changing model that can be applied in connected and autonomous vehicle systems. They use dynamic game theory and receding horizon optimal control to develop a predictive method for lane changing and car following control. Their model evaluates the continuous accelerations and lane changing process together. Based on this study, by using human driven models and estimating the response of regular vehicles, autonomous vehicles can use information from on-board sensors and make cooperative lane changing without inter-vehicle communications.

Game theoretical approach is applicable when interactions between different players exist and decision making of each player has influence on others. Since in lane changing situations, different car drivers interact with each other and cooperation of each vehicle affect the action of other drivers, game theory technique is appropriate to be used in modeling purposes of this traffic behavior.

Although several studies have investigated lane changing behavior modeling using game theory, some shortcomings such as considering broader traffic characteristics in the payoff functions of the game players still exist. This research considers the merging case as merging lane changing (MLC) and all other lane changes as discretionary lane changing (DLC). The authors develop different payoff functions for the MLC and DLC cases in the proposed model. This paper seeks to model lane changing behavior more effectively and accurately, which the authors present in detail in the following sections.

4.3 Problem definition

Lane changing modeling plays a crucial role in transportation studies because this behavior plays an important role in traffic management policies and traffic safety. Traffic projects rely on using traffic simulator tools, so investigating the factors that may affect lane changing behavior, which may improve simulation results, remains critical *(Moridpour et al., 2013)*.

As previously discussed, lane changing behavior combines the decision making process and many conflicts that happen between vehicles; therefore, game theory represents one of the best approaches for modeling lane changing due to the complexity of this process *(Zhang, 2009)*. Previous models have failed to consider some important broader traffic characteristics such as lane density. Lane density appears to play a role in the lane changing process. For instance, if a driver observes congestion downstream in the target lane, the lane change probably does not happen even if an acceptable gap exists or speed gain may occur after lane change completion. To be clearer, in the proposed modeling approach, lane density considers the driving environment beyond the surrounding vehicles and considers the drivers' evaluation of traffic congestion in the current lane and the target lane by monitoring conditions downstream of the drivers' current positions. Therefore, this study considers the density differences of the current lane and the target lanes as an element in the payoff functions of the target vehicle in discretionary lane changing process.

The contribution of this study includes:

- Considering broader traffic characteristic (lane density) into payoff functions of designed game problem.
- Conducting signaling game approach for interaction of lag and target vehicles.
- Modeling merging and discretionary lane changing behavior in one framework.

As a result, modeling lane changing behavior with game theory that investigates the effects of lag and target vehicles and also considering the broader traffic condition can improve the existing models.

4.4 Modeling Lane Changing Behavior Using Game Theory

This study models discretionary lane changing (DLC) and merging lane changing (MLC) behaviors on a freeway using a game theoretical approach. As discussed earlier, including lane density in the lane change model represents a significant improvement over existing approaches. Figures 4-2 to 4-5 represent the typical discretionary and merging lane changing process in uncongested and congested traffic situations.

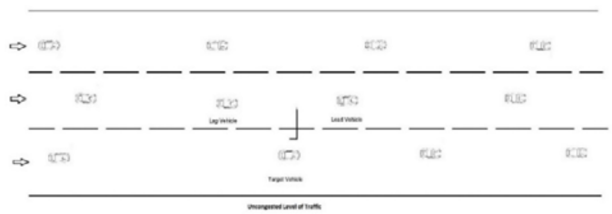


Figure 4-2. Discretionary lane changing process in uncongested traffic situation

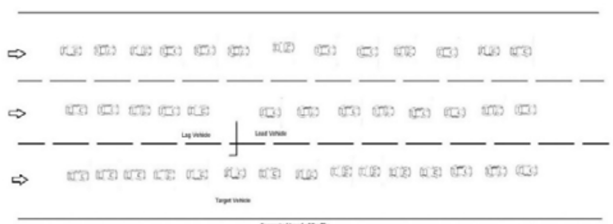


Figure 4-3. Discretionary lane changing process in congested traffic situation

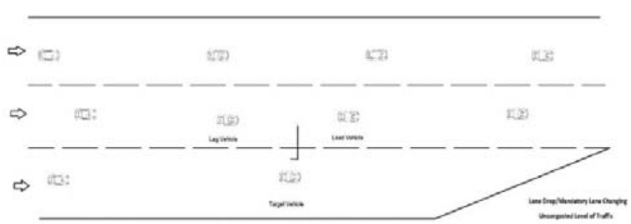


Figure 4-4. Merging lane changing process in uncongested traffic situation

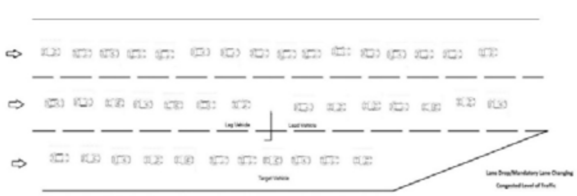


Figure 4-5. Merging lane changing process in congested traffic situation

Based on Figures 4-2 to 4-5, merging to a freeway represents a MLC, and DLC signifies all other lane changing situations. This paper expands the lane changing scenarios to include the congested and uncongested conditions for both merging and discretionary lane changes. The lane density consideration of current lane and target lane are about drivers' evaluating of traffic congestion in downstream of these lanes. These approaches to lane changing modeling is a significant contribution which can improve existing lane changing models' accuracy.

Table 4-1 presents the MLC payoff matrix and Table 4-2 shows the payoff matrix for DLC. Q_{ij} and R_{ij} indicate the payoffs of the target vehicle in the MLC and DLC situations, respectively. Additionally, M_{ij} and D_{ij} represent the payoffs of the lag vehicle in the MLC and DLC process, respectively. They require separate representations because the target vehicle has different payoff functions under MLC and DLC conditions, which section payoff function discusses in detail.

Table 4-1. Merging Lane changing behaviors game structure

	Actions	Target Vehicle	
		Change lane (T_1)	Wait for an acceptable gap (T_2)
Lag vehicle	Accelerate (L1)	(Q_{11}, M_{11})	(Q_{12}, M_{12})
	Decelerate (L_2)	(Q_{21}, M_{21})	(Q_{22}, M_{22})
	Keep Current Speed (L_3)	(Q_{31}, M_{31})	(Q_{32}, M_{32})

Table 4-2. Discretionary Lane changing behaviors game structure

	Actions	Target Vehicle	
		Change lane (T_1)	Wait for an acceptable gap (T_2)
Lag vehicle	Accelerate (L1)	(R_{11}, D_{11})	(R_{12}, D_{12})
	Decelerate (L_2)	(R_{21}, D_{21})	(R_{22}, D_{22})
	Keep Current Speed (L_3)	(R_{31}, D_{31})	(R_{32}, D_{32})

The authors model the traffic behaviors of the strategic players, target vehicle and lag vehicle, using the following notation. A target vehicle faces merging lane changing with a probability p and faces discretionary lane changing with a probability of $1 - p$, which is common knowledge for both drivers, but only the target vehicle observes the realized state of nature. After observing the state of nature (i.e., MLC or DLC) the target vehicle decides either to change lanes denoted as T_1 or wait for another acceptable gap denoted as T_2.

Without observing the target vehicle's decision (which is inspired by *Talebpour et al. (2015b)*), the lag vehicle decides to accelerate, decelerate, or keep its current speed denoted as L_1, L_2 and L_3, respectively. Figure 4-6 represents the extensive form of proposed game. This figure shows the strategic decision-makers at each of the three nodes: nature, target vehicle, and lag vehicle. The decisions are shown by the solid line and the information set is shown by the dashed line. The information set represents the fact that the lag vehicle at the time of its decision does not know the target vehicle's decision.

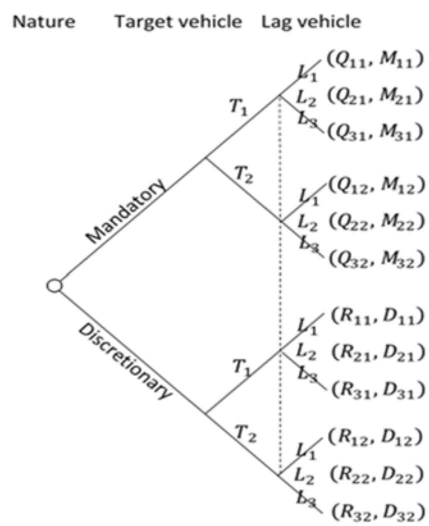


Figure 4-6. Lane changing game structure in extensive format

Based on (Barron 2013), the authors convert the extensive form of the game to a normal form of the game, which is represented in Table 4-3. The paper denotes the targeted vehicle actions as T_a^s with subscript of target vehicle action (i.e., a, which can be change lane (1) or wait for an acceptable gap (2)) and superscript of lane changing situation (i.e., s, which can be M (MLC) or D (DLC)). A tuple in each cell of Table 4-3 describes the expected payoff of the target and lag vehicle for a given column and row.

Table 4-3. Lane changing game in normal format

Action	Target Vehicle			
Lag Vehicle	T_1^M	T_1^D	T_2^M	T_2^D
L_1	$(pQ_{11}+(1-p)R_{11}$, $pM_{11}+(1-p)D_{11})$	$(pQ_{11}+(1-p)R_{12}$, $pM_{11}+(1-p)D_{12})$	$(pQ_{12}+(1-p)R_{11}$, $pM_{12}+(1-p)D_{11})$	$(pQ_{12}+(1-p)R_{12}$, $pM_{12}+(1-p)D_{12})$
L_2	$(pQ_{21}+(1-p)R_{21}$, $pM_{21}+(1-p)D_{21})$	$(pQ_{21}+(1-p)R_{22}$, $pM_{21}+(1-p)D_{22})$	$(pQ_{22}+(1-p)R_{21}$, $pM_{22}+(1-p)D_{21})$	$(pQ_{22}+(1-p)R_{22}$, $pM_{22}+(1-p)D_{22})$
L_3	$(pQ_{31}+(1-p)R_{31}$, $pM_{21}+(1-p)D_{21})$	$(pQ_{31}+(1-p)R_{32}$, $pM_{31}+(1-p)D_{32})$	$(pQ_{32}+(1-p)R_{31}$, $pM_{32}+(1-p)D_{31})$	$(pQ_{32}+(1-p)R_{32}$, $pM_{32}+(1-p)D_{32})$

4.4.1 Extensions on the Game Theoretical Model

In this section, the authors discuss two potential approaches for extending the game theoretical model. First, the current model tries to consider most common actions for both the target vehicle and the lag vehicle. This model may be extended by considering more actions; for instance, the lag vehicle can also choose to change lane as an action. Second, based on previous studies (Talebpour et al., 2015b), the current model assumes that the lag vehicle does not know the target vehicle's decision. The authors relax this assumption, and model the drivers' decisions as a *signaling game*. In signaling games, one player has more information about the state of nature than the other player. The more informed player has to decide whether to signal this piece of information, and the less informed player has to decide how to respond to the signal his opponent has sent, recognizing that signals may be strategically chosen.

In the revised model, after realizing the state of nature (i.e., MLC with probability p or DLC with probability of $(1-p)$ the target vehicle selects an action from its action set of $\{T_1, T_2\}$. The target vehicle is informed about the state of nature and can convey this information to the lag vehicle by selecting a proper action. The lag vehicle observes the target vehicle's decision and then takes an action from the set of $\{L_1, L_2, L_3\}$. The structure of drivers' decisions under this extension is presented in 4-7. The lag vehicle becomes aware of the target vehicle's decision of T_2 at the left information set (i.e., the left dashed line) and becomes aware of T_1 at the right information set (i.e., the right dashed line).

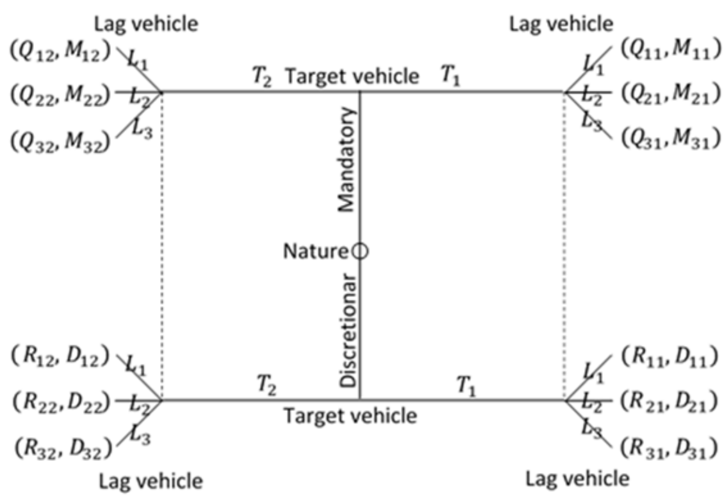


Figure 4-7. Lane changing game structure in extensive format

4.4.2 Payoff Functions

This study formulates payoff functions based on the different interests of each player and considering MLC and DLC situations while both players consider safety constraints. Additionally, the target vehicle tries to minimize the time spent in the current lane in the MLC situation as well as gain speed after a discretionary lane changing maneuver. As indicated in previous sections, lane density matters in the discretionary lane changing process. Even if the target vehicle can increase its speed in a short period of time, but congestion occurs downstream, then the target vehicle may not execute a lane change. Therefore, the target vehicle must evaluate the lane density difference between the current lane and adjacent lanes.

The lag vehicle seeks to minimize speed variation subject to safety constraints in both the MLC and DLC situations.

4.4.2.1 Payoff Function of Target Vehicle in Discretionary Lane Changing Situation

In the DLC process, the target vehicle has two actions. When this player attempts to change lanes and the lag vehicle accelerates or decelerates, the player evaluates the acceleration of target vehicle for executing the lane change and the acceleration of the lag vehicle for avoiding a collision. The target vehicle also checks the difference of speed and lane density between its current lane and the target lane. When the lag vehicle keeps its current speed, the target vehicle checks all variables mentioned above except the acceleration of lag vehicle, which is 0. The other action of the target vehicle is to not change lanes. In this situation and when the lag vehicle is accelerating or decelerating, the target vehicle evaluates the acceleration of the lag vehicle for avoiding collision, the difference of the speed and lane density between its current lane and the target lane, and the waiting time that the target vehicle spends in the current lane to find another acceptable gap. However, when the lag vehicle keeps its current speed, the target vehicle checks all the previous variables except the acceleration of lag vehicle, which is 0. Below is the payoff function formulation for target vehicle:

Eq 4-1. $R_{11}= \alpha_1+ \alpha_2A_t+ \alpha_3A_l+ \alpha_4\Delta V+ \alpha_5\Delta K+ \mu_1$

Eq 4-2. $R_{21}= \alpha_6+ \alpha_7A_t+ \alpha_8A_l+ \alpha_9\Delta V+ \alpha_{10}\Delta K+ \mu_2$

Eq 4-3. $R_{31}= \alpha_{11}+ \alpha_{12}A_t+ \alpha_{13}\Delta V+ \alpha_{14}\Delta K+ \mu_3$

Eq 4-4. $R_{12}= \alpha_{15}+ \alpha_{16}A_l+ \alpha_{17}\Delta V+ \alpha_{18}\Delta K+ \alpha_{19}t_w+ \mu_4$

Eq 4-5. $R_{22}= \alpha_{20} + \alpha_{21}A_l + \alpha_{22}\Delta V + \alpha_{23}\Delta K + \alpha_{24}t_w + \mu_5$

Eq 4-6. $R_{32}= \alpha_{25} + \alpha_{26}\Delta V + \alpha_{27}\Delta K + \alpha_{28}t_w + \mu_6$

Where:

R_{ij}= Payoff of target vehicle in DLC situation

A_t= Acceleration of target vehicle during lane changing process (ft/s^2)

A_l= Acceleration of lag vehicle to avoid collision (ft/s^2)

ΔV= Speed difference of current lane (initial lane of target vehicle) and target lane in (mi/hr)

ΔK= Lane density difference of current lane and target lane (veh/mi)

t_w= Waiting time of target vehicle to find another acceptable gap (s)

α_i= Parameters to be predicted by model calibration

μ_i= Term for finding unobserved variables

Table 4-4 shows the matrix of payoff functions of the target vehicle in DLC situation.

Table 4-4. Target Vehicle Payoff Functions in DLC process

		Target Vehicle	
Lag vehicle	Actions	Change lane (T_1)	Wait for an acceptable gap (T_2)
	Accelerate (L_1)	$\alpha_1 + \alpha_2A_t + \alpha_3A_l + \alpha_4\Delta V + \alpha_5\Delta K + \mu_1$	$\alpha_{15} + \alpha_{16}A_l + \alpha_{17}\Delta V + \alpha_{18}\Delta K + \alpha_{19}t_w + \mu_4$
	Decelerate (L_2)	$\alpha_6 + \alpha_7A_t + \alpha_8A_l + \alpha_9\Delta V + \alpha_{10}\Delta K + \mu_2$	$\alpha_{20} + \alpha_{21}A_l + \alpha_{22}\Delta V + \alpha_{23}\Delta K + \alpha_{24}t_w + \mu_5$
	Keep Current Speed(L_3)	$\alpha_{11} + \alpha_{12}A_t + \alpha_{13}\Delta V + \alpha_{14}\Delta K + \mu_3$	$\alpha_{25} + \alpha_{26}\Delta V + \alpha_{27}\Delta K + \alpha_{28}t_w + \mu_6$

4.4.2.2 Payoff Function of Target Vehicle in Merging Lane Changing Situation

In the MLC situation, when the target vehicle changes lanes and the lag vehicle accelerates or decelerates, the target vehicle observes its own acceleration as well as the lag vehicle's.

However, when the lag vehicle keeps its current speed, the target vehicle just evaluates its own acceleration. In the case of no lane change, when the lag vehicle accelerates or decelerates, the target vehicle observes the lag vehicle's acceleration as well as the waiting time in the current lane for another acceptable gap. However, when the lag vehicle keeps its current speed, the target vehicle just evaluates the waiting time in the current lane for another acceptable gap. The Q_{ij} is the payoff of target vehicle in the MLC situation. All other variables remain the same. Table 4-5 demonstrates the payoff functions for the target vehicle in MLC situation.

Eq 4-7. $Q_{11}= \alpha_{29}+ \alpha_{30}A_t+ \alpha_{31}A_l+ \mu_7$

Eq 4-8. $Q_{21}= \alpha_{32}+ \alpha_{33}A_t+ \alpha_{34}A_l+ \mu_8$

Eq 4-9. $Q_{31}= \alpha_{35}+ \alpha_{36}A_t+ \mu_9$

Eq 4-10. $Q_{12}= \alpha_{37}+ \alpha_{38}A_l+ \alpha_{39}t_w+ \mu_{10}$

Eq 4-11. $Q_{22}= \alpha_{40} + \alpha_{41}A_l +\alpha_{42}t_w+ \mu_{11}$

Eq 4-12. $Q_{32}= \alpha_{43} +\alpha_{44}t_w+ \mu_{12}$

Table 4-5. Target Vehicle Payoff Functions in MLC process

	Target Vehicle		
Lag vehicle	Actions	Change lane (T_1)	Wait for an acceptable gap (T_2)
	Accelerate (L_1)	$\alpha_{29}+ \alpha_{30}A_t+ \alpha_{31}A_l+ \mu_7$	$\alpha_{37}+ \alpha_{38}A_l+ \alpha_{39}t_w+ \mu_{10}$
	Decelerate (L_2)	$\alpha_{32}+ \alpha_{33}A_t+ \alpha_{34}A_l+ \mu_8$	$\alpha_{40} + \alpha_{41}A_l +\alpha_{42}t_w+ \mu_{11}$
	Keep Current Speed(L_3)	$\alpha_{35}+ \alpha_{36}A_t+ \mu_9$	$\alpha_{43} +\alpha_{44}t_w+ \mu_{12}$

4.4.2.3 Payoff Function of Lag Vehicle

The payoff functions of the lag vehicle do not differ in the MLC or DLC situations. During the lane changing process, the lag vehicle has three actions. When the target vehicle is changing lane and the lag vehicle accelerates or decelerates, then the lag vehicle evaluates its own acceleration as well as the target vehicle's acceleration for preventing a collision. However, when the lag vehicle keeps its current speed, the lag vehicle only evaluates the acceleration of the target vehicle. In the case where the target vehicle does not change lane and lag vehicle accelerates or decelerates, the lag vehicle evaluates its own acceleration, but when the lag vehicle keeps its current speed, a constant parameter and unobserved variables form the payoff function. M_{ij} and D_{ij} represent the lag vehicle payoffs in MLC and DLC situations, respectively while all other variables remain the same.

Eq 4-13. M_{11} or $D_{11} = \alpha_{45} + \alpha_{46}A_t + \alpha_{47}A_l + \mu_{13}$

Eq 4-14. M_{21} or $D_{21} = \alpha_{48} + \alpha_{49}A_t + \alpha_{50}A_l + \mu_{14}$

Eq 4-15. M_{31} or $D_{31} = \alpha_{51} + \alpha_{52}A_t + \mu_{15}$

Eq 4-16. M_{12} or $D_{12} = \alpha_{53} + \alpha_{54}A_l + \mu_{16}$

Eq 4-17. M_{22} or $D_{22} = \alpha_{55} + \alpha_{56}A_l + \mu_{17}$

Eq 4-18. M_{32} or $D_{32} = \alpha_{57} + \mu_{18}$

Table 4-6 shows the matrix of payoff functions for the lag vehicle.

Table 4-6. Lag Vehicle Payoff Functions

	Target Vehicle		
Lag vehicle	Actions	Change lane (T_1)	Wait for an acceptable gap (T_2)
	Accelerate (L_1)	$\alpha_{45} + \alpha_{46}A_t + \alpha_{47}A_l + \mu_{13}$	$\alpha_{53} + \alpha_{54}A_l + \mu_{16}$
	Decelerate (L_2)	$\alpha_{48} + \alpha_{49}A_t + \alpha_{50}A_l + \mu_{14}$	$\alpha_{55} + \alpha_{56}A_l + \mu_{17}$
	Keep Current Speed(L_3)	$\alpha_{51} + \alpha_{52}A_t + \mu_{15}$	$\alpha_{57} + \mu_{18}$

4.4.3 Case study on finding Perfect Bayesian Equilibrium (PBE)

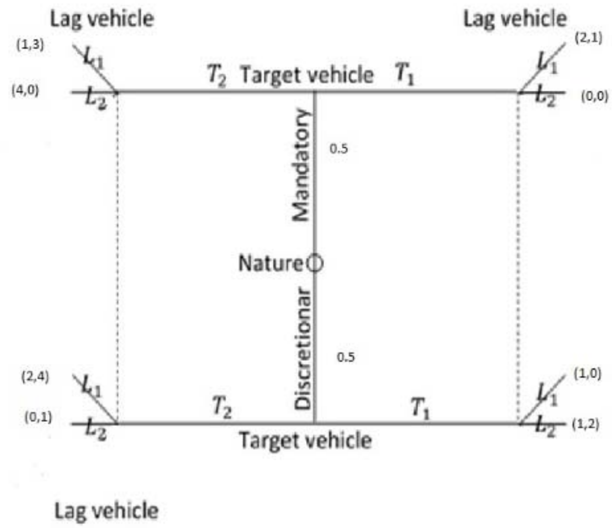


Figure 4-8: Case Study Game Structure

In this section, a case study of a signaling game is proposed. Based on outcomes of naturalistic driving behavior shown in chapter 3, the most frequent actions are maintaining speed and decelerating to cooperate with the target vehicle. Therefore, based on the state of nature (merging or discretionary), the target vehicle who is aware of the nature might change lane (T_1) or wait for an acceptable gap (T_2). The lag vehicle who observes the action of the informed agent (target vehicle) might decelerate to cooperate with the target vehicle (L_1) or maintain its speed (L_2). The two actions of lag vehicle that have significant proportions (more than 70%, based on outcomes of chapter 3), were considered to simplify the example. Figure 4-8 shows the structure of the game as well as the pay-off of both players in different conditions. Pay-offs are just numerical examples here. What can be done with trajectory data or any other sort of naturalistic driving data is finding several actions of target vehicles and reactions of lag vehicles and therefore estimating the parameters of pay-off functions and from there finding several points of pay-offs.

Note that the lag vehicle who is the receiver in the game, update its belief about the state of nature based on the strategy chosen by the target vehicle.

Players: Target vehicle (sender)

Lag vehicle (receiver)

Sender strategies: (T_1T_1, T_1T_2, T_2T_1, T_2T_2)

The first element: What the target vehicle does in merging situation.

The second element: What the target vehicle does in discretionary situation.

Receiver strategies: (L_1L_1, L_1L_2, L_2L_1, L_2L_2)

The first element: What the lag vehicle does in left information set.

The second element: What the lag vehicle does on right information set.

We assume that the prior belief of lag vehicle about the state of nature (merging/discretionary lane changing of target vehicle) is 0.5 and 0.5. Lag vehicle also assigns probability of p to discretionary lane changing if the target vehicle changes the lane immediately (T_1). She also assigns probability of q to merging lane changing if the target vehicle waits for an acceptable gap (T_2).

The study assumes that lag vehicle is not able to understand the state of the nature based on target vehicle's action, so the Pooling Bayesian Equilibrium (PBE) should be obtained and therefore we are going to consider T_1T_1 and T_2T_2 as the strategies of target vehicle.

Based on game structure shown in Figure 4-8, if the target vehicle waits for an acceptable gap in both merging and discretionary situations, then the best response of lag vehicle is to decelerate to change lane in both situations, so:

Now, consider that the lag vehicle decelerates:

Eq 4-19. $p*3+(1-p)*4=4-p$

and if the lag vehicle maintains its speed:

Eq 4-20. $p*0+(1-p)*1=1-p$

Target vehicle plays T_2T_2 , then the best response is L_1L_1.

Therefore, the pay-off of decelerating is greater than the pay-off of maintaining speed for all p.

Pay-off of L_1> Pay-off of L_2 for all p

But the question is under which condition (T_2T_2, L_1L_1) is an equilibrium?

Based on Nash equilibrium definition, the equilibrium sets of actions are the ones that the players do not have any incentives to deviate from that action.

If the ideal is to have (T_2T_2, L_1L_1) as an equilibrium, then for instance, if the target vehicle changes lane immediately (T_1) in merging lane changing situation, then the lag vehicle maintains its speed (2*0.5>1*0.5). Since, the target vehicle is aware of the nature, he/she knows that if the lag vehicle maintains its speed, then he/she earns 0 as the pay-off. Therefore, the target vehicle does not have the incentive to deviate to change lane immediately.

Now, the belief probability of the lag vehicle is calculated. If the state of nature is merging and lag vehicle decelerates (L_1), then:

Eq 4-21. $L_1=q+(1-q)*0$

Eq. 4-22. $L_2=q*0+(1-q)*2$

Therefore $q \leq 0.67$

So, the Pooling Bayesian Equilibrium (PBE) is obtained as (T_2T_2, L_1L_1, p=0.5, q=0.67)

The same procedure should be followed by considering if the target vehicle (sender) chooses T_1T_1)

4.5 Conclusion

This study proposes a model of merging and discretionary lane changing behavior in one framework. The authors introduce a more logical and realistic methodological approach for modeling lane changing behavior where the target vehicle is aware of the state of nature. The target vehicle decides whether to change lane or wait for another acceptable gap. Then, the lag vehicle also decides to accelerate (for closing the gap), decelerate (for cooperation), or to keep its current speed. In this game, the lag vehicle tries to minimize speed variation subject to safety constraints, while the target vehicle aims to minimize the time spent in its current lane as well as gaining speed under safety constraints. The authors propose the payoff functions based on these goals, for the target and lag vehicles.

This research attempts to improve existing lane changing models and create a more realistic representation of the lane changing process by considering merging scenario for MLC, the traffic congestion of current and target lanes, and also different payoff functions for the MLC and DLC situations.

The main aim of this paper is to introduce an enhanced game theory (signaling game) methodological approach for modeling lane changing behavior. This developed game theory problem does not have a closed form of solution. The authors recommend utilizing trajectory data sets or even a lab experimental design to find the optimal solution for the game problem, which is left for future research. Moreover, the game theory model requires model calibration and validation by using vehicle trajectory data or any sort of naturalistic driving data in order to be applied into traffic simulation packages.

Additionally, some shortcomings still exist such as considering the lead vehicle as a player or assuming more actions for game players, especially lag vehicle which is left for future work. Future enhancements to this model (one shot game) may consider continuous game theory application for modeling lane changing behavior and define multiple games for this behavior.

4.6 References

Agrawal, A.W., Dill, J., Nixon, H., 2010. Green transportation taxes and fees: A survey of public preferences in California. Transp. Res. Part Transp. Environ. 15, 189–196. https://doi.org/10.1016/j.trd.2009.11.003

Ahern, A.A., Tapley, N., 2008. The use of stated preference techniques to model modal choices on interurban trips in Ireland. Transp. Res. Part Policy Pract. 42, 15–27. https://doi.org/10.1016/j.tra.2007.06.005

Anand, S., Padmanabham, P., Govardhan, A., 2014. Application of Factor Analysis to k-means Clustering Algorithm on Transportation Data. https://doi.org/10.5120/16673-6677

Bajari, P., Hong, H., Ryan, S.P., 2010. Identification and Estimation of a Discrete Game of Complete Information. Econometrica 78, 1529–1568. https://doi.org/10.3982/ECTA5434

Balal, E., Cheu, R.L., Sarkodie-Gyan, T., 2016. A binary decision model for discretionary lane changing move based on fuzzy inference system. Transp. Res. Part C Emerg. Technol. 67, 47–61. https://doi.org/10.1016/j.trc.2016.02.009

Ben-Akiva, M.E., Choudhury, C., Toledo, T., 2006. Lane changing models, in: Proceedings of the International Symposium of Transport Simulation.

Bertram, D., n.d. Likert Scale \lick-urt\, n. 11.

Björklund, G.M., Åberg, L., 2005. Driver behaviour in intersections: Formal and informal traffic rules. Transp. Res. Part F Traffic Psychol. Behav. 8, 239–253. https://doi.org/10.1016/j.trf.2005.04.006

Bryant, F.B., Yarnold, P.R., Michelson, E.A., 1999. Statistical Methodology. Acad. Emerg. Med. 6, 54–66. https://doi.org/10.1111/j.1553-2712.1999.tb00096.x

Cao, X., Young, W., Sarvi, M., 2013. Exploring Duration of Lane Change Execution 17.

Choudhury, C., Ben-Akiva, M.E., Toledo, T., Rao, A., Lee, G., 2007. State dependence in lane changing models. Elsevier.

Clifton, K.J., Handy, S.L., 2003. Qualitative Methods in Travel Behaviour Research, in: Transport Survey Quality and Innovation. Emerald Group Publishing Limited, pp. 283–302. https://doi.org/10.1108/9781786359551-016

Coifman, B., Cassidy, M., 2002. Vehicle reidentification and travel time measurement on congested freeways. Transp. Res. Part Policy Pract. 36, 899–917. https://doi.org/10.1016/S0965-8564(01)00046-5

Collins, A., Rose, J., Hess, S., 2007. Stated Preference survey design in air travel choice behaviour modelling. Proc. Eur. Transp. Conf. 2007 HELD 17-19 Oct. 2007 LEIDEN Neth.

Dill, J., Voros, K., 2007. Factors Affecting Bicycling Demand: Initial Survey Findings from the Portland, Oregon, Region. Transp. Res. Rec. J. Transp. Res. Board 2031, 9–17. https://doi.org/10.3141/2031-02

Dula, C.S., Geller, E.S., 2003. Risky, aggressive, or emotional driving: Addressing the need for consistent communication in research. J. Safety Res. 34, 559–566. https://doi.org/10.1016/j.jsr.2003.03.004

Errampalli, M., Okushima, M., Akiyama, T., n.d. Lane Change Modelling with Fuzzy Logic in Microscopic Traffic Simulation 6.

Flamm, B.J., Agrawal, A.W., 2012. Constraints to green vehicle ownership: A focus group study. Transp. Res. Part Transp. Environ. 17, 108–115. https://doi.org/10.1016/j.trd.2011.09.013

Fletcher, C.N., Garasky, S.B., Jensen, H.H., Nielsen, R.B., 2010. Transportation Access: A Key Employment Barrier for Rural Low-Income Families. J. Poverty 14, 123–144. https://doi.org/10.1080/10875541003711581

Gan, H., Ye, X., 2012. Urban freeway user' diversion response to variable message sign displaying the travel time of both freeway and local street. IET Intell. Transp. Syst. 6, 78–86. https://doi.org/10.1049/iet-its.2011.0070

Gipps, P.G., 1986. A model for the structure of lane-changing decisions. Transp. Res. Part B Methodol. 20, 403–414. https://doi.org/10.1016/0191-2615(86)90012-3

Glasgow, N., Blakely, R.M., 2000. Older Nonmetropolitan Residents' Evaluations of Their Transportation Arrangements. J. Appl. Gerontol. 19, 95–116. https://doi.org/10.1177/073346480001900106

Golob, T.F., Regan, A.C., 2001. Impacts of highway congestion on freight operations: perceptions of trucking industry managers. Transp. Res. Part Policy Pract. 35, 577–599. https://doi.org/10.1016/S0965-8564(00)00008-2

Greenwood, M., Kendrick, T., Davies, H., Gill, F.J., 2017. Hearing voices: Comparing two methods for analysis of focus group data. Appl. Nurs. Res. ANR 35, 90–93. https://doi.org/10.1016/j.apnr.2017.02.024

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2014. Multivariate data analysis.

Hayley, A.C., Ridder, B. de, Stough, C., Ford, T.C., Downey, L.A., 2017. Emotional intelligence and risky driving behaviour in adults. Transp. Res. Part F Traffic Psychol. Behav. 49, 124–131. https://doi.org/10.1016/j.trf.2017.06.009

Hidas, P., 2005. Modelling vehicle interactions in microscopic simulation of merging and weaving. Transp. Res. Part C Emerg. Technol. 13, 37–62. https://doi.org/10.1016/j.trc.2004.12.003

Hidas, P., 2002. Modelling lane changing and merging in microscopic traffic simulation. Transp. Res. Part C Emerg. Technol. 10, 351–371. https://doi.org/10.1016/S0968-090X(02)00026-8

Huth, V., Füssl, E., Risser, R., 2014. Motorcycle riders' perceptions, attitudes and strategies: Findings from a focus group study. Transp. Res. Part F Traffic Psychol. Behav. 25, 74–85. https://doi.org/10.1016/j.trf.2014.05.004

k proportions test [WWW Document], n.d. . Xlstat Your Data Anal. Solut. URL https://www.xlstat.com/en/solutions/features/comparison-of-k-proportions (accessed 2.24.19).

Kesting, A., Treiber, M., Helbing, D., 2007. General Lane-Changing Model MOBIL for Car-Following Models. Transp. Res. Rec. J. Transp. Res. Board 1999, 86–94. https://doi.org/10.3141/1999-10

Keyvan-Ekbatani, M., Knoop, V.L., Daamen, W., 2016a. Categorization of the lane change decision process on freeways. Transp. Res. Part C Emerg. Technol. 69, 515–526. https://doi.org/10.1016/j.trc.2015.11.012

Keyvan-Ekbatani, M., Knoop, V.L., Daamen, W., 2016b. Categorization of the lane change decision process on freeways. Transp. Res. Part C Emerg. Technol. 69, 515–526. https://doi.org/10.1016/j.trc.2015.11.012

Kita, H., 1999. A merging–giveway interaction model of cars in a merging section: a game theoretic analysis. Transp. Res. Part Policy Pract. 33, 305–312. https://doi.org/10.1016/S0965-8564(98)00039-1

Knight, W., n.d. Why Cars Won't be Driverless Anytime Soon [WWW Document]. MIT Technol. Rev. URL https://www.technologyreview.com/s/513531/proceed-with-caution-toward-the-self-driving-car/ (accessed 9.23.18).

Knoop, V.L., Keyvan-Ekbatani, M., de Baat, M., Taale, H., Hoogendoorn, S.P., 2018. Lane Change Behavior on Freeways: An Online Survey Using Video Clips [WWW Document]. J. Adv. Transp. https://doi.org/10.1155/2018/9236028

Kondyli, A., Elefteriadou, L., 2011. Modeling Driver Behavior at Freeway-Ramp Merges. Transp. Res. Rec. J. Transp. Res. Board 2249, 29–37. https://doi.org/10.3141/2249-05

Kondyli, A., Elefteriadou, L., 2009. Driver Behavior at Freeway-Ramp Merging Areas. Transp. Res. Rec. J. Transp. Res. Board 2124, 157–166. https://doi.org/10.3141/2124-15

Kusuma, A., Liu, R., Choudhury, C., Montgomery, F., 2015. Lane-Changing Characteristics at Weaving Section. Presented at the Transportation Research Board 94th Annual MeetingTransportation Research Board.

Lei, P.-W., Wu, Q., 2007. Introduction to Structural Equation Modeling: Issues and Practical Considerations. Educ. Meas. Issues Pract. 26, 33–43. https://doi.org/10.1111/j.1745-3992.2007.00099.x

Li Gen, Sun Lu, Pan Yiyong, Yu Ye, n.d. Analysis of Merging Behavior Parameters Using NGSIM Data Sets. CICTP 2016, Proceedings. https://doi.org/10.1061/9780784479896.008

Li, Z., Hensher, D.A., 2012. Congestion charging and car use: A review of stated preference and opinion studies and market monitoring evidence. Transp. Policy, URBAN TRANSPORT INITIATIVES 20, 47–61. https://doi.org/10.1016/j.tranpol.2011.12.004

Liu, H., Xin, W., Adam, Z., Ban, X.J., 2007. A game theoretical approach for modelling merging and yielding behaviour at freeway on-ramp sections, in: 17th International Symposium on Transportation and Traffic Theory, London, UK.

Loo, B.P.Y., 2002. Role of Stated Preference Methods in Planning for Sustainable Urban Transportation: State of Practice and Future Prospects. J. Urban Plan. Dev. 128, 210–224. https://doi.org/10.1061/(ASCE)0733-9488(2002)128:4(210)

Machado-León, J.L., de Oña, J., de Oña, R., Eboli, L., Mazzulla, G., 2016. Socio-economic and driving experience factors affecting drivers’ perceptions of traffic crash risk. Transp. Res. Part F Traffic Psychol. Behav. 37, 41–51. https://doi.org/10.1016/j.trf.2015.11.010

Marczak, F., Daamen, W., Buisson, C., 2013. Merging behaviour: Empirical comparison between two sites and new theory development. Transp. Res. Part C Emerg. Technol. 36, 530–546. https://doi.org/10.1016/j.trc.2013.07.007

Moridpour, S., Sarvi, M., Rose, G., 2013. Lane changing models: a critical review. Transp. Lett.

Ortúzar, J. de D., Iacobelli, A., Valeze, C., 2000. Estimating demand for a cycle-way network. Transp. Res. Part Policy Pract. 34, 353–373. https://doi.org/10.1016/S0965-8564(99)00040-3

Peeta, S., Ramos, J.L., 2006. Driver response to variable message signs-based traffic information. IEE Proc. - Intell. Transp. Syst. 153, 2. https://doi.org/10.1049/ip-its:20055012

Peeta, S., Zhang, P., Zhou, W., 2005. Behavior-based analysis of freeway car–truck interactions and related mitigation strategies. Transp. Res. Part B Methodol. 39, 417–451. https://doi.org/10.1016/j.trb.2004.06.002

Peng, J., Guo, Y., Fu, R., Yuan, W., Wang, C., 2015. Multi-parameter prediction of drivers’ lane-changing behaviour with neural network model. Appl. Ergon. 50, 207–217. https://doi.org/10.1016/j.apergo.2015.03.017

Rahman, M., Chowdhury, M., Xie, Y., He, Y., 2013. Review of Microscopic Lane-Changing Models and Future Research Opportunities. IEEE Trans. Intell. Transp. Syst. 14, 1942–1956. https://doi.org/10.1109/TITS.2013.2272074

Rayle, L., Dai, D., Chan, N., Cervero, R., Shaheen, S., 2016. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transp. Policy 45, 168–178. https://doi.org/10.1016/j.tranpol.2015.10.004

Razo, M., Gao, S., 2013. A rank-dependent expected utility model for strategic route choice with stated preference data. Transp. Res. Part C Emerg. Technol., Selected papers from the Seventh Triennial Symposium on Transportation Analysis (TRISTAN VII) 27, 117–130. https://doi.org/10.1016/j.trc.2011.08.009

Razo, M., Gao, S., 2010. Strategic Thinking and Risk Attitudes in Route Choice. Transp. Res. Rec. J. Transp. Res. Board 2156, 28–35. https://doi.org/10.3141/2156-04

Salvucci, D.D., n.d. Inferring Driver Intent: A Case Study in Lane-Change Detection. Th Annu. Meet. 4.

Sarvi, M., Kuwahara, M., 2007. Microsimulation of Freeway Ramp Merging Processes Under Congested Traffic Conditions. IEEE Trans. Intell. Transp. Syst. 8, 470–479. https://doi.org/10.1109/TITS.2007.895305

Schakel, W., Knoop, V., van Arem, B., 2012. Integrated Lane Change Model with Relaxation and Synchronization. Transp. Res. Rec. J. Transp. Res. Board 2316, 47–57. https://doi.org/10.3141/2316-06

Stathopoulos, A., Valeri, E., Marcucci, E., 2012. Stakeholder reactions to urban freight policy innovation. J. Transp. Geogr., Special Section on Rail Transit Systems and High Speed Rail 22, 34–45. https://doi.org/10.1016/j.jtrangeo.2011.11.017

Stinson, M., Bhat, C., 2003. Commuter Bicyclist Route Choice: Analysis Using a Stated Preference Survey. Transp. Res. Rec. J. Transp. Res. Board 1828, 107–115. https://doi.org/10.3141/1828-13

Sun, Daniel(Jian), Elefteriadou, L., 2011. Lane-changing behavior on urban streets: A focus group-based study. Appl. Ergon. 42, 682–691. https://doi.org/10.1016/j.apergo.2010.11.001

Sun, Daniel, Elefteriadou, L., 2011. Information Categorization Based on Driver Behavior for Urban Lane-Changing Maneuvers. Transp. Res. Rec. J. Transp. Res. Board 2249, 89–94. https://doi.org/10.3141/2249-11

Sun, D., Elefteriadou, L., 2010. Research and Implementation of Lane-Changing Model Based on Driver Behavior. Transp. Res. Rec. J. Transp. Res. Board 2161, 1–10. https://doi.org/10.3141/2161-01

Sun, D. (Jian), Kondyli, A., 2010. Modeling Vehicle Interactions during Lane-Changing Behavior on Arterial Streets. Comput.-Aided Civ. Infrastruct. Eng. 25, 557–571. https://doi.org/10.1111/j.1467-8667.2010.00679.x

Sun, D.J., 2009. A lane-changing model for urban arterial streets (Ph.D.). University of Florida, United States -- Florida.

Svenson, A.L., Gawron, V.J., Brown, T., n.d. General Dynamics.

Talebpour, A., Mahmassani, H.S., Hamdar, S.H., 2015a. Modeling lane-changing behavior in a connected environment: A game theory approach. Transp. Res. Part C Emerg. Technol., Special Issue on International Symposium on Transportation and Traffic Theory 59, 216–232. https://doi.org/10.1016/j.trc.2015.07.007

Talebpour, A., Mahmassani, H.S., Hamdar, S.H., 2015b. Modeling lane-changing behavior in a connected environment: A game theory approach. Transp. Res. Procedia 7, 420–440.

Tashakkori, A., Teddlie, C., Teddlie, C.B., 2003. Handbook of Mixed Methods in Social & Behavioral Research. SAGE.

Toledo, T., Koutsopoulos, H.N., Ben-Akiva, M.E., 2003. Modeling Integrated Lane-Changing Behavior. Transp. Res. Rec. J. Transp. Res. Board 1857, 30–38. https://doi.org/10.3141/1857-04

Wagh, S.T., Razvi, N.A., 2016. Marascuilo Method of Multiple Comparisons (An Analytical Study of Caesarean Section Delivery) 3, 4.

Wang, M., Hoogendoorn, S.P., Daamen, W., van Arem, B., Happee, R., 2015. Game theoretic approach for predictive lane-changing and car-following control. Transp. Res. Part C Emerg. Technol. 58, Part A, 73–92. https://doi.org/10.1016/j.trc.2015.07.009

Wardman, M., 1988. A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour. J. Transp. Econ. Policy 22, 71–91.

Washbrook, K., Haider, W., Jaccard, M., 2006. Estimating commuter mode choice: A discrete choice analysis of the impact of road pricing and parking charges. Transportation 33, 621–639. https://doi.org/10.1007/s11116-005-5711-x

Yao, S., 2015. Game theoretical approach on vehicle-cyclist interaction analysis.

Yim, Y., Khattak, A., Raw, J., 2002. Traveler Response to New Dynamic Information Sources: Analyzing Corridor and Areawide Behavioral Surveys. Transp. Res. Rec. J. Transp. Res. Board 1803, 66–75. https://doi.org/10.3141/1803-10

Zhang, Z., n.d. Analysis of the Traffic Behavior Based on Game Theory, in: International Conference on Transportation Engineering 2009. American Society of Civil Engineers, pp. 501–506.

Chapter 5

Conclusion

5.1 Outcome of the Study

This study uses a mixed methodological approach to derive forty different discretionary lane change stimuli. The study clusters the discretionary lane changing reasons based on Confirmatory Factor Analysis which is discussed in details in appendix C. The study also clusters the factors using data driven approach (EFA technique), so three clusters named "peripheral, subjective and temporal" categories identified. The "peripheral" cluster seems to cause drivers to change lane significantly more than other two clusters. The importance of each factor within each cluster is also investigated by generating the z-score associated to each factor. Lastly, the importance of lane changing factors, regardless of the categories were identified by generating z-scores. The outcomes of this section can be used for (1) enhancing discretionary lane changing models by considering lane changing clusters into models and (2) improving roads' safety for all users by knowing the factors and clusters that have more impact on lane changing initiation.

After identifying discretionary lane changing stimuli, the study investigates the suitability of stated preference data for calibrating lane changing behavior. Due to the complexity of the lane changing action and the roles involved, this study focuses its effort on identifying and characterizing the actions for the target, lead and lag vehicles. The SP and RP lane changing data four cases that represent the combinations across the geometry (merging or discretionary) and congestion (uncongested or congested) dimensions. The SP data indicates that the geometry and congestion levels do not impact driver behavior; however, the naturalistic driving data shows that the congestion level impacts driver behavior. Based on RP indications, as a target vehicle, people change lanes immediately more often in uncongested situations. The drivers as lead vehicle seem to accelerate to cooperate with the target vehicle much more during uncongested situations and people more decelerate to cooperate with the target vehicle in congested situations, but they keep their current speed in uncongested situations. The RP data currently confirms the SP findings that geometry does not play a significant role in driver behavior, but the naturalistic driving data has a limited sample size for the merging case. These discrepancies in the results between the two data sets, and the confirmatory hypothesis tests that compare the proportion of drivers choosing different actions in the two data sets demonstrate that SP data represents a weak to misleading substitute for other data sources. The author recommends the use of trajectory and naturalistic driving data for future lane changing studies.

Using the actions of vehicles involved in the lane changing process, the author models merging and discretionary lane changing behaviors in one framework using a game theoretical approach. The goal of this phase is to consider interactions of vehicles during lane changings into a model without making non-logical assumptions to simplify the model. Therefore, game theoretical approach is chosen in this phase to propose a methodological model of lane changing behavior. The target vehicle which is aware of the state of nature decides whether to change lane or wait for another acceptable gap. Then, the lag vehicle also decides to accelerate (for closing the gap), decelerate (for cooperation), or to keep its current speed. The three most important actions of lag vehicles are chosen for modeling purpose. In this game, the lag vehicle tries to minimize speed variation subject to safety constraints (for maximizing their payoff functions), while the target vehicle aims to minimize the time spent in its current lane as well as gaining speed under safety constraints (for maximizing their payoff functions). The authors propose the payoff functions based on these goals, for the target and lag vehicles. This research attempts to improve existing lane changing models and create a more realistic representation of the lane changing process by considering merging scenario for MLC, the traffic congestion of current and target lanes, and also different payoff functions for the MLC and DLC situations.

5.2 Recommendations for Future Direction

This research requires significant enhancements before it achieves technology readiness level 9.

- This research can be strengthened by collecting a large sample of real-world lane changing behaviors. A larger sample would improve the understanding of the real actions of drivers. Furthermore, the revealed preferences can be obtained via vehicles' trajectory data such as NGSIM data set and then compared to stated preferences. The comprehensive naturalistic driving behavior data such as SHRP2 data sets are also can be used for such studies. The data which are used for the purpose of this study should be able to capture the instantaneous actions of vehicles involved in lane changing process target, lead and lag vehicles). The acceleration, deceleration, keeping current speed and changing lane of lead and lag vehicle as well as target vehicle' actions (changing lane immediately and waiting for an acceptable gap) should has to be observed by the potential real-world data.

- The factors identified in this study need to be investigated using trajectory, naturalistic driving and/or driving simulator data to determine the probabilities of specific factors or combinations of factors stimulating lane changes. These data sources need to be used to determine the probability of the actions of drivers while in the target, lead and lag roles. Integrating these two features together can create a comprehensive lane changing model; however, integrating the comprehensive lane changing model with a car following model poses further complications. As a first step, future researchers need to develop an experimental design to explore discretionary lane changing stimuli in detail and the role that the origin-destination pair plays in prompting lane changes.
- The game theoretical model requires calibration and validation. The calibration process seems likely to work best with naturalistic driving or trajectory data. The game theoretical lane changing model requires full integration with the findings from the mixed methods effort, and its application requires integration into a microscopic or mesoscopic traffic simulation software. A comprehensive lane changing model may prove useful for the future control of autonomous vehicles and represents a significant challenge for fundamental traffic flow theory.

Appendix A: Survey Questions of Lane Changing Factors

Demographic questions

1- How old are you? *(18-23, 24-29, 30-35, 36-41, 42-47, 48 or older)*
2- What is your gender? *(Male, Female, Prefer not to answer*)
3- What is your level of education? (*Some high school/no diploma, High school graduate, Some college credit/no degree, Associate degree, Bachelor's degree, Master's degree, Professional degree, Doctorate degree)*
4- How many years have you been driving a vehicle? *(Less than a year, 1-5 years, 6-10 years, More than 10 years)*
5- How long have you been driving in the US? *(Less than a year, 1-5 years, 5-10 years, More than 10 years)*
6- How often do you drive on freeway*? (More than two times in a week, One or two times in a week, One or two times in a month, Once a month or less)*
7- What is your race? *(White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or Pacific Islander, Other)*
8- How much is your annual income? *(Less than 15000$), 16000$-25000$, 26000$-35000$, 36000$-45000$, 46000$-55000$, 56000$-65000$, more than 65000$)*
9- What is your type of vehicle? *(Sedan, Truck, SUV, Hatchback, Full size van)*
10- How old is your vehicle? *(Less than a year, 1-3 years, 3-5 yeas, 5-10 years, 10-20 years, older than 20 years)*
11- Does your car have lane departure/blind spot feature? *(Yes, No)*

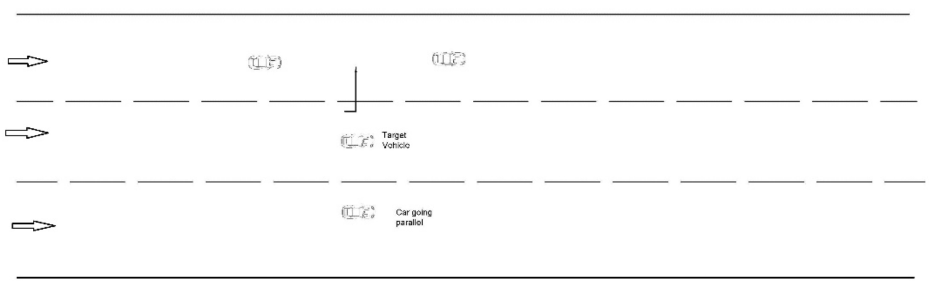
Lane changing factors

12- What is your decision for changing lane in the following situations?

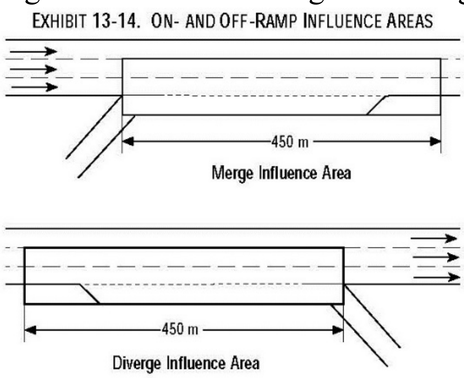
Choices for question 12: (Strongly Agree, Agree, Somewhat Agree, Neither Agree nor Disagree, Somewhat Disagree, Disagree, Strongly Disagree)

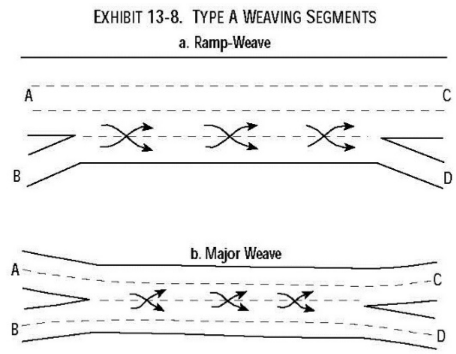
- Changing lane in order to gain speed
- Changing lane for passing a slow vehicle
- Changing lane because I am driving using a zig/zag or weaving technique.
- Changing lane because of being in a rush; I need to be someplace soon (e.g. in the morning for going to work).
- Changing lane because of crossing a train track in order to be in a better and safe situation.
- Changing lane because there are a lot of sharp curves.
- Changing lane on curves in order to have more space and be safe.

- Changing lane because a car is going parallel to your car.



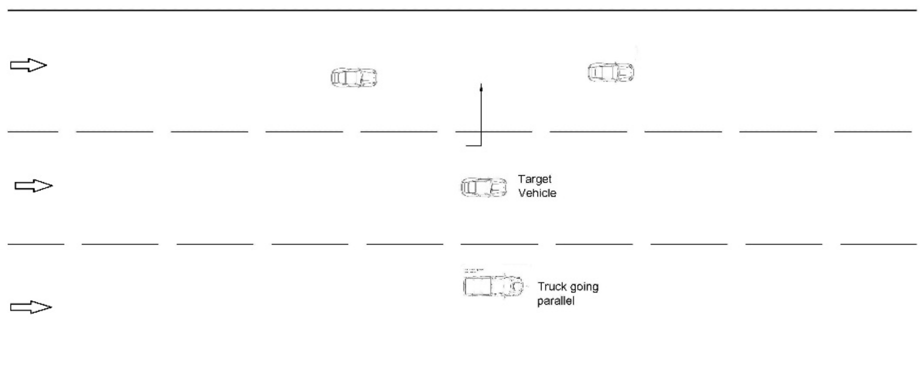
- Changing lane because of being in weaving, merging or diverging area.





- Changing lane due to being familiar with the road.
- Changing lane when your car is not in a good condition. (When car does not steer or brake well)
- Changing lane at night time.
- Changing lane when sleepy (e.g. in the morning when you go to work and you are sleepy)
- Changing lane because a car is parked or stopped on the shoulder.
- Changing lane because of any kind of distraction (Listening to the radio, using GPS, seeing billboards, talking on the phone, someone is talking to you, etc)
- Changing lane because a vehicle in front of you keeps braking or brakes for no reason.
- Changing lane because of seeing a police car. (e.g. police care with radar on the shoulder or police car moving in a freeway)
- Changing lane when the weather is rainy, snowy and windy.
- Changing lane to avoid being in the right most lane when water is accumulated in that lane because of rain.
- Changing lane to the middle lane to avoid other vehicles' lane changing or merging.
- Changing lane when there is congestion downstream in your lane (Lane Density matters)
- Changing lane because of bad pavement condition or because the road is bumpy.
- Changing lane in heavy traffic.
- Changing lane because an emergency vehicle is parked or stopped on the shoulder.
- Changing lane with newer car or smaller and more flexible car. (Type or model of the car matters)

- Changing lane because of object in your lane.(e.g. seeing a dead animal or a piece of lumber)
- Changing lane for going to the lanes that are not allowed for trucks.
- Changing lane because of having a good mood (e.g. listening to a music or being excited)
- Changing lane in order to pass a truck or a heavy vehicle even if those vehicles go fast.
- Changing lane when a truck or a heavy vehicle is beside you in the adjacent lane.



- Changing lane in areas that drivers are more aggressive such as New York or Mexico city (Location matters)
- Changing lane to avoid a hazard such as fire along one side of a road.
- Changing lane because somebody is tailgating you.
- Changing lane because the car in front of you produces lots of smoke and blocks your view.
- Changing lane to provide the left lane for other vehicles to pass you.
- Changing lane because a car is parked or stopped on the shoulder (because of having a flat tire or something is wrong with their cars) and people are observed outside of the vehicle.
- Changing lane because a vehicle behind you flashes its headlights.
- Changing lane if a truck with something in it like mattress is in front of you and you do not feel safe.
- Changing lane because people in another vehicle are fighting or crying. (You think their behavior might not be normal)
- Changing lane to go to shoulder of freeway or exit from freeway when something suddenly happens to your car.
- Changing lane based on what other people in your car ask you to do.
- Changing lane because another driver is on the phone.
- Changing lane because of lane blockage.(e.g. stalled car in your lane)

Appendix B: LISREL Outputs of CFA Analysis

DATE: 2/ 6/2019
TIME: 11:06

L I S R E L 10.1 (64 Bit)

BY

Karl G. Jöreskog & Dag Sörbom

This program is published exclusively by
Scientific Software International, Inc.
http://www.ssicentral.com

The following lines were read from file C:\Users\somyh\Desktop\Test2\test20.SPJ:

Raw Data from file 'C:\Users\somyh\Desktop\Test2\LaneChange4.LSF'

Total Sample Size(N) = 220

Univariate Marginal Parameters

Variable	Mean	St. Dev.	Thresholds					
Q12	0.946	1.191	0.000	1.000	1.555	2.356	2.680	3.439
Q15	1.362	1.364	0.000	1.000	1.675	2.361	2.723	3.605
Q16	0.606	1.215	0.000	1.000	1.307	2.044	2.335	2.786
Q17	1.387	1.526	0.000	1.000	1.702	2.647	3.194	3.898
Q18	1.016	1.415	0.000	1.000	1.777	2.278	2.568	3.227
Q21	1.016	1.386	0.000	1.000	1.636	2.723	2.946	3.788
Q22	0.971	1.273	0.000	1.000	1.638	2.602	3.186	3.977
Q23	0.982	1.554	0.000	1.000	1.562	2.421	2.858	3.538
Q24	1.509	1.107	0.000	1.000	1.471	2.820	3.330	3.953
Q25	1.923	1.561	0.000	1.000	1.490	2.524	2.867	3.736
Q26	0.339	1.045	0.000	1.000	1.577	2.349	3.066	
Q27	2.246	1.972	0.000	1.000	1.535	2.677	3.306	4.450
Q28	0.178	1.300	0.000	1.000	1.631	2.376	2.677	2.899
Q29	0.653	1.592	0.000	1.000	1.508	2.432	2.870	3.509
Q30	1.387	1.526	0.000	1.000	1.684	2.647	3.194	3.772
Q31	0.538	1.238	0.000	1.000	1.540	2.300	2.692	3.271
Q32	0.929	1.242	0.000	1.000	1.548	2.372	2.588	3.030
Q33	0.721	0.891	0.000	1.000	1.322	2.080	2.320	2.826
Q34	0.463	1.201	0.000	1.000	1.554	2.387	2.618	3.114
Q35	1.208	1.210	0.000	1.000	1.529	2.207	2.613	3.379
Q36	-0.124	1.362	0.000	1.000	1.398	2.116	2.600	3.093
Q37	2.028	1.780	0.000	1.000	1.784	3.305	3.872	4.879
Q38	-0.114	1.432	0.000	1.000	1.517	2.882	3.267	
Q39	1.015	1.278	0.000	1.000	1.491	2.558	2.834	3.836
Q40	2.534	1.859	0.000	1.000	1.726	2.983	3.437	4.390
Q41	1.469	1.444	0.000	1.000	1.767	2.571	3.212	4.358
Q42	1.349	1.377	0.000	1.000	1.698	2.530	3.187	3.677
Q43	1.358	1.412	0.000	1.000	1.600	2.741	3.132	3.816
Q44	-0.033	1.469	0.000	1.000	1.461	2.383	2.791	3.437
Q45	0.567	1.200	0.000	1.000	1.464	1.987	2.441	2.792
Q46	0.261	1.195	0.000	1.000	1.572	2.176	2.900	3.084
Q47	0.513	1.057	0.000	1.000	1.474	2.166	2.354	2.727
Q48	0.142	1.245	0.000	1.000	1.457	2.377	2.891	
Q49	1.220	1.199	0.000	1.000	1.524	2.395	2.821	3.193
Q50	0.225	1.311	0.000	1.000	1.636	2.848	2.969	3.322
Q51	0.956	1.279	0.000	1.000	1.481	2.233	2.700	3.182
Q52	0.194	1.304	0.000	1.000	1.424	2.338	2.700	3.072
Q53	2.162	1.586	0.000	1.000	1.723	2.490	2.932	3.837
Q54	0.885	1.258	0.000	1.000	1.681	2.435	2.759	3.402
Q55	0.163	1.296	0.000	1.000	1.456	2.566	3.223	3.543

Univariate Distributions for Ordinal Variables

Q12	Frequency	Percentage	Bar Chart
1	47	21.4	
2	67	30.5	
3	39	17.7	
4	41	18.6	
5	10	4.5	
6	12	5.5	
7	4	1.8	

Q15 Frequency Percentage Bar Chart

1	35	15.9
2	52	23.6
3	43	19.5
4	39	17.7
5	16	7.3
6	24	10.9
7	11	5.0

Q16	Frequency	Percentage	Bar Chart
1	68	30.9	
2	70	31.8	
3	20	9.1	
4	36	16.4	
5	9	4.1	
6	9	4.1	
7	8	3.6	

Q17	Frequency	Percentage	Bar Chart
1	40	18.2	
2	48	21.8	
3	40	18.2	
4	47	21.4	
5	19	8.6	
6	15	6.8	
7	11	5.0	

Q18	Frequency	Percentage	Bar Chart
1	52	23.6	
2	57	25.9	
3	46	20.9	
4	24	10.9	
5	11	5.0	
6	17	7.7	
7	13	5.9	

Q21	Frequency	Percentage	Bar Chart
1	51	23.2	
2	58	26.4	
3	39	17.7	
4	48	21.8	
5	6	2.7	
6	13	5.9	
7	5	2.3	

Q22	Frequency	Percentage	Bar Chart
1	49	22.3	
2	63	28.6	
3	42	19.1	
4	44	20.0	
5	13	5.9	
6	7	3.2	
7	2	0.9	

Q23	Frequency	Percentage	Bar Chart
1	58	26.4	
2	53	24.1	
3	31	14.1	
4	39	17.7	
5	14	6.4	
6	14	6.4	
7	11	5.0	

Q24	Frequency	Percentage	Bar Chart
1	19	8.6	
2	52	23.6	
3	36	16.4	
4	87	39.5	
5	15	6.8	
6	8	3.6	
7	3	1.4	

Q25	Frequency	Percentage	Bar Chart
1	24	10.9	
2	37	16.8	
3	25	11.4	
4	57	25.9	
5	17	7.7	
6	33	15.0	
7	27	12.3	

Q26	Frequency	Percentage	Bar Chart
1	82	37.3	
2	80	36.4	
3	32	14.5	
4	20	9.1	

5	5	2.3
6	1	0.5

Q27	Frequency	Percentage	Bar Chart
1	28	12.7	
2	30	13.6	
3	21	9.5	
4	50	22.7	
5	26	11.8	
6	36	16.4	
7	29	13.2	

Q28	Frequency	Percentage	Bar Chart
1	98	44.5	
2	64	29.1	
3	29	13.2	
4	19	8.6	
5	4	1.8	
6	2	0.9	
7	4	1.8	

Q29	Frequency	Percentage	Bar Chart
1	75	34.1	
2	54	24.5	
3	26	11.8	
4	36	16.4	
5	11	5.0	
6	10	4.5	
7	8	3.6	

Q30	Frequency	Percentage	Bar Chart
1	40	18.2	
2	48	21.8	
3	39	17.7	
4	48	21.8	
5	19	8.6	
6	13	5.9	
7	13	5.9	

Q31	Frequency	Percentage	Bar Chart
1	73	33.2	
2	69	31.4	
3	32	14.5	
4	29	13.2	
5	8	3.6	
6	6	2.7	
7	3	1.4	

Q32	Frequency	Percentage	Bar Chart
1	50	22.7	
2	65	29.5	
3	37	16.8	
4	41	18.6	
5	7	3.2	
6	10	4.5	
7	10	4.5	

Q33	Frequency	Percentage	Bar Chart
1	46	20.9	
2	91	41.4	
3	28	12.7	
4	41	18.6	
5	6	2.7	
6	6	2.7	
7	2	0.9	

Q34	Frequency	Percentage	Bar Chart
1	77	35.0	
2	71	32.3	
3	32	14.5	
4	28	12.7	
5	4	1.8	
6	5	2.3	
7	3	1.4	

Q35	Frequency	Percentage	Bar Chart
1	35	15.9	
2	60	27.3	
3	38	17.3	
4	42	19.1	
5	18	8.2	
6	19	8.6	
7	8	3.6	

Q36 Frequency Percentage Bar Chart

1	118	53.6	
2	57	25.9	
3	16	7.3	
4	18	8.2	
5	6	2.7	
6	3	1.4	
7	2	0.9	

Q37	Frequency	Percentage	Bar Chart
1	28	12.7	
2	34	15.5	
3	36	16.4	
4	70	31.8	
5	19	8.6	
6	21	9.5	
7	12	5.5	

Q38	Frequency	Percentage	Bar Chart
1	117	53.2	
2	55	25.0	
3	20	9.1	
4	24	10.9	
5	2	0.9	
6	2	0.9	

Q39	Frequency	Percentage	Bar Chart
1	47	21.4	
2	62	28.2	
3	33	15.0	
4	53	24.1	
5	8	3.6	
6	14	6.4	
7	3	1.4	

Q40	Frequency	Percentage	Bar Chart
1	19	8.6	
2	26	11.8	
3	28	12.7	
4	58	26.4	
5	20	9.1	
6	34	15.5	
7	35	15.9	

Q41	Frequency	Percentage	Bar Chart
1	34	15.5	
2	48	21.8	
3	46	20.9	
4	43	19.5	
5	24	10.9	
6	20	9.1	
7	5	2.3	

Q42	Frequency	Percentage	Bar Chart
1	36	16.4	
2	52	23.6	
3	44	20.0	
4	45	20.5	
5	23	10.5	
6	10	4.5	
7	10	4.5	

Q43	Frequency	Percentage	Bar Chart
1	37	16.8	
2	51	23.2	
3	37	16.8	
4	59	26.8	
5	13	5.9	
6	14	6.4	
7	9	4.1	

Q44	Frequency	Percentage	Bar Chart
1	112	50.9	
2	55	25.0	
3	19	8.6	
4	23	10.5	
5	5	2.3	
6	4	1.8	
7	2	0.9	

Q45	Frequency	Percentage	Bar Chart
1	70	31.8	
2	71	32.3	
3	29	13.2	
4	24	10.9	
5	13	5.9	

6	6	2.7
7	7	3.2

Q46	Frequency	Percentage	Bar Chart
1	91	41.4	
2	70	31.8	
3	29	13.2	
4	18	8.2	
5	9	4.1	
6	1	0.5	
7	2	0.9	

Q47	Frequency	Percentage	Bar Chart
1	69	31.4	
2	80	36.4	
3	31	14.1	
4	27	12.3	
5	4	1.8	
6	5	2.3	
7	4	1.8	

Q48	Frequency	Percentage	Bar Chart
1	100	45.5	
2	66	30.0	
3	22	10.0	
4	24	10.9	
5	5	2.3	
6	3	1.4	

Q49	Frequency	Percentage	Bar Chart
1	34	15.5	
2	60	27.3	
3	38	17.3	
4	52	23.6	
5	16	7.3	
6	9	4.1	
7	11	5.0	

Q50	Frequency	Percentage	Bar Chart
1	95	43.2	
2	64	29.1	
3	30	13.6	
4	26	11.8	
5	1	0.5	
6	2	0.9	
7	2	0.9	

Q51	Frequency	Percentage	Bar Chart
1	50	22.7	
2	63	28.6	
3	32	14.5	
4	40	18.2	
5	16	7.3	
6	10	4.5	
7	9	4.1	

Q52	Frequency	Percentage	Bar Chart
1	97	44.1	
2	64	29.1	
3	21	9.5	
4	27	12.3	
5	5	2.3	
6	3	1.4	
7	3	1.4	

Q53	Frequency	Percentage	Bar Chart
1	19	8.6	
2	32	14.5	
3	35	15.9	
4	42	19.1	
5	23	10.5	
6	37	16.8	
7	32	14.5	

Q54	Frequency	Percentage	Bar Chart
1	53	24.1	
2	65	29.5	
3	44	20.0	
4	34	15.5	
5	9	4.1	
6	10	4.5	
7	5	2.3	

Q55	Frequency	Percentage	Bar Chart
1	99	45.0	

```
       2       64          29.1
       3       22          10.0
       4       28          12.7
       5        5           2.3
       6        1           0.5
       7        1           0.5

 There are 218 distinct response patterns, see FREQ-file.
 The 20 most common patterns are :
       2          4    4    4    4    4    4    4    4    4    4    4    4    4    4    4
                  4    4    4    4    4    4    4    4    4    4    4    4    4    4    4
                  4    4    4    4    4    4    4    4    4    4
       2          1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
                  1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
                  1    1    1    1    1    1    1    1    1    1
       1          2    3    7    6    6    1    7    1    5    6    1    7    1    6    7
                  1    7    6    2    7    1    7    1    1    7    2    1    6    1    1
                  2    3    1    6    1    7    1    7    3    1
       1          7    7    6    6    3    6    3    2    6    7    3    6    3    6    6
                  3    5    4    3    5    2    6    3    6    6    4    3    6    2    3
                  3    2    6    6    6    6    3    6    6    2
       1          4    4    4    4    4    4    4    4    4    6    4    4    4    4    4
                  4    4    4    4    2    1    4    1    4    4    4    4    4    4    4
                  4    4    4    4    4    4    4    4    4    4
       1          3    4    3    1    3    2    3    3    2    2    3    2    1    2    3
                  3    3    5    3    7    2    3    2    2    3    2    2    2    3    2
                  3    3    2    4    4    1    2    3    1    3
       1          2    3    6    3    3    4    2    2    3    2    3    5    2    5    5
                  3    4    4    2    4    2    4    4    6    6    5    2    5    2    5
                  2    1    3    3    3    2    2    6    2    5
       1          3    2    1    1    2    3    1    2    3    5    1    2    3    2    1
                  3    2    4    2    2    2    1    2    1    2    3    2    3    2    2
                  2    1    1    3    3    1    1    2    3    1
       1          1    1    1    7    1    1    1    1    4    7    1    1    1    1    7
                  7    1    1    7    1    1    7    1    1    1    1    7    7    1    1
                  7    1    1    1    1    1    1    1    1    1
       1          4    4    4    4    2    6    4    2    4    4    1    4    2    2    4
                  4    3    3    3    3    1    4    1    3    4    3    2    3    1    2
                  3    2    2    3    3    3    2    4    2    2
       1          2    4    2    3    5    4    3    2    5    6    2    6    4    1    4
                  3    2    2    4    4    2    4    2    4    7    2    4    4    1    2
                  2    4    1    2    2    4    2    6    2    2
       1          4    4    1    4    7    3    6    2    4    7    2    6    1    1    2
                  3    2    4    2    5    2    1    2    1    2    5    3    6    4    2
                  6    1    4    2    2    3    1    7    4    3
       1          2    2    4    3    4    2    2    2    2    7    4    6    1    4    3
                  2    2    3    1    2    3    4    1    6    4    2    4    4    1    2
                  2    1    3    1    1    5    1    2    2    1
       1          1    1    1    1    7    1    2    6    4    7    1    1    1    1    7
                  1    2    1    1    1    1    6    1    7    7    1    1    7    1    1
                  1    1    1    1    1    1    1    2    1    1
       1          3    3    4    6    7    2    1    1    5    7    1    7    1    1    7
                  1    7    1    1    3    2    7    1    1    7    3    2    2    1    2
                  1    7    2    7    1    1    1    6    1    2
       1          5    3    2    2    2    4    2    5    4    4    1    4    1    4    5
                  1    1    2    2    4    1    2    1    4    4    5    2    5    1    2
                  1    2    1    3    1    2    1    3    2    1
       1          3    3    2    3    1    2    3    4    2    6    2    3    2    2    2
                  3    3    2    2    2    2    5    3    2    4    3    2    2    1    3
                  1    2    2    3    1    5    3    3    2    3
       1          4    3    3    3    4    2    4    3    3    4    2    2    3    4    3
                  2    3    3    3    3    3    3    3    3    4    3    3    4    3    4
                  4    4    2    5    3    2    4    3    3    4
       1          1    1    2    1    1    1    2    2    2    2    1    2    2    1    1
                  1    1    2    1    1    1    1    1    1    2    2    1    2    1    1
                  2    1    1    1    1    1    1    2    1    1
       1          3    6    3    6    2    6    2    3    4    6    2    4    2    3    6
                  2    2    3    2    3    2    2    2    2    6    5    5    6    2    2
                  1    1    2    2    2    2    2    6    2    3

 Means

                   Q12       Q15       Q16       Q17       Q18       Q21
              --------  --------  --------  --------  --------  --------
                 0.946     1.362     0.606     1.387     1.016     1.016

 Means

                   Q22       Q23       Q24       Q25       Q26       Q27
              --------  --------  --------  --------  --------  --------
                 0.971     0.982     1.509     1.923     0.339     2.246

 Means

                   Q28       Q29       Q30       Q31       Q32       Q33
```

0.178	0.653	1.387	0.538	0.929	0.721

Means

Q34	Q35	Q36	Q37	Q38	Q39
0.463	1.208	-0.124	2.028	-0.114	1.015

Means

Q40	Q41	Q42	Q43	Q44	Q45
2.534	1.469	1.349	1.358	-0.033	0.567

Means

Q46	Q47	Q48	Q49	Q50	Q51
0.261	0.513	0.142	1.220	0.225	0.956

Means

Q52	Q53	Q54	Q55
0.194	2.162	0.885	0.163

Standard Deviations

Q12	Q15	Q16	Q17	Q18	Q21
1.191	1.364	1.215	1.526	1.415	1.386

Standard Deviations

Q22	Q23	Q24	Q25	Q26	Q27
1.273	1.554	1.107	1.561	1.045	1.972

Standard Deviations

Q28	Q29	Q30	Q31	Q32	Q33
1.300	1.592	1.526	1.238	1.242	0.891

Standard Deviations

Q34	Q35	Q36	Q37	Q38	Q39
1.201	1.210	1.362	1.780	1.432	1.278

Standard Deviations

Q40	Q41	Q42	Q43	Q44	Q45
1.859	1.444	1.377	1.412	1.469	1.200

Standard Deviations

Q46	Q47	Q48	Q49	Q50	Q51
1.195	1.057	1.245	1.199	1.311	1.279

Standard Deviations

Q52	Q53	Q54	Q55
1.304	1.586	1.258	1.296

```
Latent Variables  Environmental Safety Emotional Temporal
Relationships
Q17 = Environmental
Q21 = Environmental
Q22 = Environmental
Q29 = Environmental
Q30 = Environmental
Q31 = Environmental
Q34 = Environmental
Q43 = Environmental
Q46 = Environmental
Q51 = Environmental
Q53 = Environmental
Q55 = Environmental
Q16 = Safety
Q18 = Safety
```

```
Q23 = Safety
Q25 = Safety
Q26 = Safety
Q28 = Safety
Q32 = Safety
Q36 = Safety
Q38 = Safety
Q41 = Safety
Q42 = Safety
Q44 = Safety
Q45 = Safety
Q47 = Safety
Q48 = Safety
Q49 = Safety
Q50 = Safety
Q52 = Safety
Q54 = Safety
Q12 = Temporal
Q15 = Temporal
Q24 = Temporal
Q33 = Temporal
Q35 = Temporal
Q39 = Temporal
Q27 = Emotional
Q37 = Emotional
Q40 = Emotional
Path Diagram
End of Problem

Sample Size =   220
```

Covariance Matrix

	Q12	Q15	Q16	Q17	Q18	Q21
Q12	1.419					
Q15	0.744	1.861				
Q16	0.239	0.257	1.476			
Q17	0.402	0.932	0.599	2.330		
Q18	0.504	0.369	0.548	0.796	2.003	
Q21	0.687	0.777	0.380	0.661	0.623	1.921
Q22	0.511	0.679	0.419	0.735	0.741	0.464
Q23	0.488	0.605	0.007	0.477	0.561	0.632
Q24	0.593	0.543	0.301	0.694	0.665	0.632
Q25	0.326	0.553	0.407	1.189	0.817	0.390
Q26	0.300	0.143	0.449	0.286	0.342	0.450
Q27	0.613	0.954	0.692	1.611	0.837	0.321
Q28	0.563	0.464	0.329	0.173	0.303	0.764
Q29	0.693	0.596	0.414	0.412	0.529	0.527
Q30	0.370	0.816	0.482	1.172	0.780	0.492
Q31	0.295	0.246	0.464	0.430	0.354	0.700
Q32	0.448	0.532	0.525	0.693	0.577	0.705
Q33	0.497	0.461	0.259	0.241	0.344	0.550
Q34	0.507	0.365	0.433	0.387	0.450	0.599
Q35	0.519	0.774	0.439	0.696	0.488	0.439
Q36	0.520	0.152	0.289	0.136	0.266	0.732
Q37	0.448	0.916	0.806	1.327	0.481	0.682
Q38	0.513	0.087	0.633	0.114	0.407	0.847
Q39	0.313	0.367	0.418	0.514	0.606	0.599
Q40	0.491	1.126	0.642	1.489	0.854	0.400
Q41	0.758	0.855	0.269	0.696	0.454	0.780
Q42	0.226	0.559	0.385	0.801	0.518	0.436
Q43	0.497	0.749	0.179	0.768	0.547	0.730
Q44	0.429	0.057	0.644	0.146	0.586	0.867
Q45	0.439	0.587	0.496	0.590	0.341	0.603
Q46	0.442	0.299	0.420	0.301	0.364	0.686
Q47	0.398	0.356	0.463	0.358	0.226	0.535
Q48	0.574	0.135	0.430	0.080	0.408	0.714
Q49	0.517	0.493	0.621	0.706	0.567	0.488
Q50	0.512	0.436	0.534	0.389	0.452	0.847
Q51	0.437	0.401	0.561	0.451	0.430	0.577
Q52	0.530	0.274	0.531	0.211	0.383	0.778
Q53	0.648	1.126	0.472	1.124	0.811	0.504
Q54	0.376	0.325	0.545	0.614	0.548	0.518
Q55	0.414	0.207	0.399	0.061	0.395	0.757

Covariance Matrix

	Q22	Q23	Q24	Q25	Q26	Q27
Q22	1.619					
Q23	0.753	2.414				
Q24	0.460	0.449	1.225			

Q25	0.684	0.808	0.661	2.438		
Q26	0.495	0.096	0.206	-0.014	1.092	
Q27	0.882	0.526	0.729	1.600	-0.014	3.887
Q28	0.587	0.410	0.305	-0.192	0.702	0.015
Q29	0.742	0.505	0.677	0.731	0.699	0.739
Q30	0.753	0.564	0.770	1.150	0.276	1.209
Q31	0.313	0.308	0.488	0.003	0.548	0.208
Q32	0.501	0.335	0.459	0.383	0.439	0.605
Q33	0.444	0.363	0.308	0.070	0.272	0.259
Q34	0.722	0.478	0.283	0.210	0.574	0.109
Q35	0.552	0.332	0.422	0.662	0.090	0.889
Q36	0.542	0.191	0.378	-0.133	0.797	-0.165
Q37	0.734	0.474	0.789	1.359	-0.032	1.779
Q38	0.468	0.727	0.278	-0.221	0.801	-0.344
Q39	0.361	0.462	0.436	0.468	0.489	0.709
Q40	0.750	0.736	0.827	1.543	-0.149	2.410
Q41	0.572	0.461	0.623	0.674	0.249	1.036
Q42	0.596	0.450	0.413	0.823	0.238	1.163
Q43	0.448	0.727	0.586	0.976	0.215	0.746
Q44	0.681	0.544	0.377	-0.234	1.043	-0.341
Q45	0.450	0.401	0.248	0.172	0.542	0.263
Q46	0.497	0.397	0.331	0.088	0.650	-0.237
Q47	0.329	0.263	0.290	0.106	0.402	-0.059
Q48	0.468	0.384	0.381	-0.008	0.853	-0.036
Q49	0.627	0.413	0.460	0.677	0.143	0.983
Q50	0.782	0.575	0.460	0.087	0.701	0.135
Q51	0.675	0.176	0.353	0.311	0.429	0.659
Q52	0.600	0.518	0.269	0.066	0.671	-0.080
Q53	0.692	0.555	0.699	1.129	0.069	1.831
Q54	0.683	0.438	0.318	0.412	0.598	0.671
Q55	0.592	0.645	0.239	-0.113	0.756	-0.166

Covariance Matrix

	Q28	Q29	Q30	Q31	Q32	Q33
Q28	1.690					
Q29	0.542	2.534				
Q30	0.407	0.691	2.330			
Q31	0.765	0.228	0.587	1.532		
Q32	0.517	0.658	0.561	0.601	1.544	
Q33	0.553	0.475	0.329	0.355	0.419	0.794
Q34	0.907	0.536	0.577	0.684	0.462	0.489
Q35	0.093	0.496	0.723	0.104	0.279	0.344
Q36	0.962	0.644	0.215	0.853	0.297	0.474
Q37	-0.060	0.769	0.993	0.385	0.555	0.154
Q38	1.111	0.603	0.245	0.922	0.521	0.523
Q39	0.423	0.506	0.759	0.432	0.387	0.274
Q40	-0.261	0.678	1.185	0.022	0.621	0.198
Q41	0.407	0.666	0.835	0.355	0.478	0.435
Q42	0.428	0.408	0.646	0.338	0.180	0.148
Q43	0.481	0.742	1.303	0.464	0.608	0.405
Q44	1.227	0.530	0.319	0.959	0.557	0.544
Q45	0.752	0.231	0.519	0.642	0.578	0.327
Q46	0.879	0.441	0.325	0.796	0.481	0.494
Q47	0.508	0.322	0.418	0.391	0.507	0.340
Q48	0.937	0.782	0.298	0.717	0.492	0.502
Q49	0.279	0.456	0.474	0.313	0.612	0.300
Q50	1.064	0.649	0.523	0.782	0.481	0.636
Q51	0.431	0.501	0.635	0.541	0.466	0.221
Q52	0.997	0.273	0.167	0.741	0.501	0.463
Q53	-0.014	0.947	0.898	0.063	0.759	0.328
Q54	0.660	0.609	0.516	0.638	0.486	0.335
Q55	1.054	0.491	0.381	0.780	0.432	0.578

Covariance Matrix

	Q34	Q35	Q36	Q37	Q38	Q39
Q34	1.442					
Q35	0.214	1.464				
Q36	0.675	0.033	1.855			
Q37	0.179	0.742	0.019	3.167		
Q38	0.932	0.140	0.956	-0.198	2.050	
Q39	0.395	0.170	0.356	0.675	0.470	1.633
Q40	-0.101	0.953	-0.399	2.044	-0.388	0.500
Q41	0.510	0.603	0.426	0.957	0.370	0.457
Q42	0.439	0.335	0.160	0.893	0.377	0.528
Q43	0.461	0.641	0.142	0.730	0.398	0.528
Q44	1.044	0.040	1.335	-0.229	1.502	0.406
Q45	0.445	0.349	0.535	0.398	0.749	0.436
Q46	0.837	0.059	0.979	0.093	0.935	0.153
Q47	0.389	0.236	0.533	0.457	0.600	0.384
Q48	0.719	0.093	0.963	0.010	1.101	0.350
Q49	0.373	0.538	0.205	0.909	0.208	0.271

Q50	0.751	0.277	0.987	0.096	1.233	0.463
Q51	0.618	0.462	0.597	0.645	0.441	0.422
Q52	0.719	0.222	1.046	0.188	1.037	0.552
Q53	0.253	0.959	-0.166	1.550	-0.035	0.491
Q54	0.687	0.289	0.717	0.474	0.572	0.467
Q55	0.890	0.047	0.986	-0.191	1.290	0.490

Covariance Matrix

	Q40	Q41	Q42	Q43	Q44	Q45
Q40	3.455					
Q41	1.010	2.085				
Q42	0.869	0.771	1.896			
Q43	0.928	0.745	0.630	1.995		
Q44	-0.683	0.342	0.301	0.282	2.159	
Q45	0.384	0.326	0.492	0.392	0.889	1.439
Q46	-0.253	0.297	0.228	0.341	1.266	0.558
Q47	0.082	0.200	0.174	0.299	0.559	0.394
Q48	-0.161	0.195	0.191	0.313	1.244	0.564
Q49	0.771	0.629	0.618	0.442	0.276	0.461
Q50	0.062	0.516	0.547	0.580	1.329	0.685
Q51	0.534	0.352	0.209	0.477	0.583	0.282
Q52	-0.156	0.297	0.258	0.276	1.292	0.764
Q53	1.881	0.899	0.721	0.823	-0.131	0.434
Q54	0.418	0.661	0.449	0.414	0.838	0.360
Q55	-0.438	0.313	0.287	0.402	1.394	0.679

Covariance Matrix

	Q46	Q47	Q48	Q49	Q50	Q51
Q46	1.429					
Q47	0.418	1.118				
Q48	0.904	0.506	1.551			
Q49	0.150	0.469	0.221	1.438		
Q50	0.932	0.468	0.968	0.572	1.719	
Q51	0.570	0.299	0.432	0.474	0.340	1.635
Q52	0.919	0.561	0.982	0.381	0.947	0.499
Q53	0.038	0.295	0.086	0.866	0.231	0.542
Q54	0.774	0.330	0.630	0.445	0.765	0.635
Q55	0.862	0.528	1.070	0.334	1.067	0.425

Covariance Matrix

	Q52	Q53	Q54	Q55
Q52	1.700			
Q53	0.110	2.515		
Q54	0.667	0.557	1.584	
Q55	1.058	-0.023	0.565	1.679

Total Variance = 75.116 Generalized Variance = 0.0225

Largest Eigenvalue = 22.346 Smallest Eigenvalue = 0.116

Condition Number = 13.897
MATRIX DLT BEFORE CALLING CHI2SUBE

1.500	0.000	0.000	0.000
0.000	0.000	0.000	0.000
0.000	0.000	0.000	0.000
0.000	0.000	0.000	0.000
0.000	0.000	0.000	0.000

Number of Iterations = 25

LISREL Estimates (Maximum Likelihood)

Measurement Equations

```
     Q12 = 0.750*Temporal, Errorvar.= 0.857  , R² = 0.396
Standerr  (0.0773)                (0.0920)
Z-values   9.697                   9.310
P-values   0.000                   0.000

     Q15 = 0.881*Temporal, Errorvar.= 1.084 , R² = 0.417
Standerr  (0.0880)                (0.118)
Z-values   10.017                  9.199
P-values   0.000                   0.000
```

```
     Q16 = 0.519*Safety, Errorvar.= 1.207 , R² = 0.182
Standerr  (0.0802)                (0.117)
Z-values   6.475                   10.340
P-values   0.000                   0.000

     Q17 = 0.613*Environm, Errorvar.= 1.954 , R² = 0.161
Standerr  (0.101)                   (0.189)
Z-values   6.062                     10.365
P-values   0.000                     0.000

     Q18 = 0.489*Safety, Errorvar.= 1.763 , R² = 0.120
Standerr  (0.0950)                (0.170)
Z-values   5.149                   10.389
P-values   0.000                   0.000

     Q21 = 0.875*Environm, Errorvar.= 1.156 , R² = 0.398
Standerr  (0.0856)                  (0.114)
Z-values   10.224                    10.098
P-values   0.000                     0.000

     Q22 = 0.758*Environm, Errorvar.= 1.044 , R² = 0.355
Standerr  (0.0796)                  (0.103)
Z-values   9.524                     10.164
P-values   0.000                     0.000

     Q23 = 0.493*Safety, Errorvar.= 2.171 , R² = 0.101
Standerr  (0.105)                 (0.209)
Z-values   4.703                   10.402
P-values   0.000                   0.000

     Q24 = 0.708*Temporal, Errorvar.= 0.724  , R² = 0.409
Standerr  (0.0716)                  (0.0783)
Z-values   9.889                     9.244
P-values   0.000                     0.000

     Q25 = 0.0893*Safety, Errorvar.= 2.430 , R² = 0.00327
Standerr  (0.108)                  (0.232)
Z-values   0.825                    10.462
P-values   0.409                    0.000

     Q26 = 0.757*Safety, Errorvar.= 0.520  , R² = 0.524
Standerr  (0.0618)                (0.0528)
Z-values   12.243                  9.848
P-values   0.000                   0.000

     Q27 = 1.472*Emotiona, Errorvar.= 1.721 , R² = 0.557
Standerr  (0.122)                   (0.214)
Z-values   12.035                    8.050
P-values   0.000                     0.000

     Q28 = 0.982*Safety, Errorvar.= 0.726  , R² = 0.570
Standerr  (0.0756)                (0.0747)
Z-values   12.987                  9.721
P-values   0.000                   0.000

     Q29 = 0.744*Environm, Errorvar.= 1.980 , R² = 0.219
Standerr  (0.104)                   (0.192)
Z-values   7.172                     10.318
P-values   0.000                     0.000

     Q30 = 0.691*Environm, Errorvar.= 1.853 , R² = 0.205
Standerr  (0.0999)                  (0.179)
Z-values   6.917                     10.330
P-values   0.000                     0.000

     Q31 = 0.763*Environm, Errorvar.= 0.950  , R² = 0.380
Standerr  (0.0769)                  (0.0938)
Z-values   9.922                     10.128
P-values   0.000                     0.000

     Q32 = 0.559*Safety, Errorvar.= 1.232 , R² = 0.202
Standerr  (0.0815)                (0.119)
Z-values   6.854                   10.323
P-values   0.000                   0.000

     Q33 = 0.538*Temporal, Errorvar.= 0.505  , R² = 0.364
Standerr  (0.0584)                  (0.0534)
Z-values   9.200                     9.465
P-values   0.000                     0.000

     Q34 = 0.804*Environm, Errorvar.= 0.795  , R² = 0.448
Standerr  (0.0729)                  (0.0795)
Z-values   11.027                    10.004
P-values   0.000                     0.000
```

```
     Q35 = 0.659*Temporal, Errorvar.= 1.030 , R² = 0.297
Standerr  (0.0810)                (0.106)
Z-values   8.135                   9.736
P-values   0.000                   0.000

     Q36 = 0.961*Safety, Errorvar.= 0.931  , R² = 0.498
Standerr  (0.0813)              (0.0940)
Z-values   11.825                9.909
P-values   0.000                 0.000

     Q37 = 1.262*Emotiona, Errorvar.= 1.573 , R² = 0.503
Standerr  (0.112)                 (0.183)
Z-values   11.266                  8.577
P-values   0.000                   0.000

     Q38 = 1.104*Safety, Errorvar.= 0.831  , R² = 0.594
Standerr  (0.0825)              (0.0862)
Z-values   13.377                9.643
P-values   0.000                 0.000

     Q39 = 0.557*Temporal, Errorvar.= 1.323 , R² = 0.190
Standerr  (0.0883)                (0.131)
Z-values   6.311                   10.064
P-values   0.000                   0.000

     Q40 = 1.617*Emotiona, Errorvar.= 0.840 , R² = 0.757
Standerr  (0.110)                 (0.172)
Z-values   14.744                  4.877
P-values   0.000                   0.000

     Q41 = 0.434*Safety, Errorvar.= 1.897 , R² = 0.0903
Standerr  (0.0978)              (0.182)
Z-values   4.439                 10.409
P-values   0.000                 0.000

     Q42 = 0.381*Safety, Errorvar.= 1.751 , R² = 0.0764
Standerr  (0.0936)              (0.168)
Z-values   4.067                 10.418
P-values   0.000                 0.000

     Q43 = 0.633*Environm, Errorvar.= 1.594 , R² = 0.201
Standerr  (0.0925)                (0.154)
Z-values   6.841                   10.334
P-values   0.000                   0.000

     Q44 = 1.279*Safety, Errorvar.= 0.523  , R² = 0.758
Standerr  (0.0793)              (0.0601)
Z-values   16.120                8.702
P-values   0.000                 0.000

     Q45 = 0.688*Safety, Errorvar.= 0.965  , R² = 0.329
Standerr  (0.0757)              (0.0947)
Z-values   9.086                 10.190
P-values   0.000                 0.000

     Q46 = 0.830*Environm, Errorvar.= 0.740  , R² = 0.482
Standerr  (0.0718)                (0.0746)
Z-values   11.559                  9.928
P-values   0.000                   0.000

     Q47 = 0.526*Safety, Errorvar.= 0.842  , R² = 0.247
Standerr  (0.0684)              (0.0819)
Z-values   7.685                 10.281
P-values   0.000                 0.000

     Q48 = 0.955*Safety, Errorvar.= 0.639  , R² = 0.588
Standerr  (0.0719)              (0.0661)
Z-values   13.277                9.664
P-values   0.000                 0.000

     Q49 = 0.386*Safety, Errorvar.= 1.289 , R² = 0.104
Standerr  (0.0809)              (0.124)
Z-values   4.771                 10.400
P-values   0.000                 0.000

     Q50 = 1.030*Safety, Errorvar.= 0.657  , R² = 0.618
Standerr  (0.0749)              (0.0688)
Z-values   13.759                9.558
P-values   0.000                 0.000

     Q51 = 0.621*Environm, Errorvar.= 1.249 , R² = 0.236
Standerr  (0.0829)                (0.121)
Z-values   7.494                   10.302
P-values   0.000                   0.000
```

```
     Q52 = 0.970*Safety, Errorvar.= 0.759  , R^2 = 0.554
Standerr  (0.0763)              (0.0777)
Z-values   12.718                9.769
P-values   0.000                 0.000

     Q53 = 0.545*Environm, Errorvar.= 2.218 , R^2 = 0.118
Standerr  (0.106)                  (0.213)
Z-values   5.126                    10.396
P-values   0.000                    0.000

     Q54 = 0.714*Safety, Errorvar.= 1.074 , R^2 = 0.322
Standerr  (0.0796)              (0.105)
Z-values   8.961                 10.200
P-values   0.000                 0.000

     Q55 = 0.908*Environm, Errorvar.= 0.855  , R^2 = 0.491
Standerr  (0.0776)                 (0.0863)
Z-values   11.702                   9.906
P-values   0.000                    0.000


        Correlation Matrix of Independent Variables

           Environm    Safety   Emotiona   Temporal
           --------  --------   --------   --------
Environm      1.000

  Safety      0.937     1.000
            (0.018)
             52.034

Emotiona      0.305     0.000      1.000
            (0.073)   (0.076)
              4.164    -0.002

Temporal      0.833     0.590      0.627      1.000
            (0.039)   (0.057)    (0.059)
             21.222    10.385     10.653


W_A_R_N_I_N_G: Matrix above is not positive definite

                              Log-likelihood Values

                          Estimated Model          Saturated Model
                          ---------------          ---------------
Number of free parameters(t)        86                        820
-2ln(L)                      10901.992                   7965.413
AIC (Akaike, 1974)*          11073.992                   9605.413
BIC (Schwarz, 1978)*         11365.844                  12388.187

*LISREL uses AIC= 2t - 2ln(L) and BIC = tln(N)- 2ln(L)


                              Goodness-of-Fit Statistics

Degrees of Freedom for (C1)-(C2)                          734
Maximum Likelihood Ratio Chi-Square (C1)                  2936.580 (P = 0.0000)
Browne's (1984) ADF Chi-Square (C2_NT)                    4143.375 (P = 0.0000)

Estimated Non-centrality Parameter (NCP)                  2202.580
90 Percent Confidence Interval for NCP                    (2039.511 ; 2373.134)

Minimum Fit Function Value                                13.348
Population Discrepancy Function Value (F0)                10.012
90 Percent Confidence Interval for F0                     (9.271 ; 10.787)
Root Mean Square Error of Approximation (RMSEA)           0.117
90 Percent Confidence Interval for RMSEA                  (0.112 ; 0.121)
P-Value for Test of Close Fit (RMSEA < 0.05)              0.000

Expected Cross-Validation Index (ECVI)                    14.130
90 Percent Confidence Interval for ECVI                   (13.389 ; 14.905)
ECVI for Saturated Model                                  7.455
ECVI for Independence Model                               27.444

Chi-Square for Independence Model (780 df)            5957.731

Normed Fit Index (NFI)                                    0.507
Non-Normed Fit Index (NNFI)                               0.548
Parsimony Normed Fit Index (PNFI)                         0.477
Comparative Fit Index (CFI)                               0.575
Incremental Fit Index (IFI)                               0.578
Relative Fit Index (RFI)                                  0.476
```

Critical N (CN)	62.606

Root Mean Square Residual (RMR)	0.325
Standardized RMR	0.149
Goodness of Fit Index (GFI)	0.515
Adjusted Goodness of Fit Index (AGFI)	0.458
Parsimony Goodness of Fit Index (PGFI)	0.461

The Modification Indices Suggest to Add the

Path to	from	Decrease in Chi-Square	New Estimate
Q15	Environm	17.8	-0.69
Q15	Safety	17.5	-0.46
Q15	Emotiona	9.7	0.37
Q16	Environm	16.0	0.94
Q16	Emotiona	28.6	0.43
Q16	Temporal	11.5	0.36
Q17	Safety	57.9	-2.30
Q17	Emotiona	68.8	0.91
Q17	Temporal	47.5	1.40
Q18	Environm	33.4	1.64
Q18	Emotiona	30.8	0.54
Q18	Temporal	32.5	0.73
Q22	Safety	13.2	-0.83
Q22	Emotiona	16.9	0.34
Q22	Temporal	10.3	0.49
Q23	Environm	20.2	1.41
Q23	Emotiona	17.5	0.45
Q23	Temporal	20.1	0.64
Q25	Environm	70.9	2.79
Q25	Emotiona	80.7	1.02
Q25	Temporal	64.5	1.20
Q29	Safety	9.3	-0.94
Q29	Temporal	9.1	0.62
Q30	Safety	42.3	-1.93
Q30	Emotiona	39.6	0.67
Q30	Temporal	40.1	1.26
Q31	Safety	10.0	0.69
Q31	Temporal	11.3	-0.49
Q32	Environm	28.2	1.26
Q32	Emotiona	27.3	0.43
Q32	Temporal	27.2	0.56
Q33	Environm	29.1	0.58
Q33	Safety	31.0	0.40
Q33	Emotiona	33.0	-0.45
Q34	Safety	12.0	0.71
Q34	Emotiona	15.4	-0.29
Q34	Temporal	9.0	-0.41
Q35	Environm	13.4	-0.55
Q35	Safety	14.0	-0.37
Q35	Emotiona	12.7	0.39
Q38	Environm	11.8	-0.70
Q38	Emotiona	12.7	-0.25
Q38	Temporal	10.8	-0.30
Q41	Environm	62.2	2.31
Q41	Emotiona	51.1	0.72
Q41	Temporal	62.6	1.05
Q42	Environm	29.7	1.54
Q42	Emotiona	40.5	0.62
Q42	Temporal	24.9	0.63
Q43	Safety	29.8	-1.50
Q43	Emotiona	22.3	0.47
Q43	Temporal	31.2	1.03
Q44	Environm	56.8	-1.31
Q44	Emotiona	53.5	-0.44
Q44	Temporal	54.3	-0.58
Q45	Environm	9.0	0.64
Q45	Emotiona	10.8	0.24
Q46	Safety	50.6	1.42
Q46	Emotiona	48.1	-0.50
Q46	Temporal	47.0	-0.92
Q49	Environm	46.8	1.66
Q49	Emotiona	48.9	0.58
Q49	Temporal	43.4	0.72
Q53	Safety	100.3	-3.21
Q53	Emotiona	103.2	1.18
Q53	Temporal	88.2	2.02
Q54	Environm	11.3	0.75
Q54	Emotiona	18.0	0.33
Q54	Temporal	9.0	0.30
Q55	Safety	79.9	1.92
Q55	Emotiona	75.6	-0.67
Q55	Temporal	75.2	-1.25

The Modification Indices Suggest to Add an Error Covariance

Between	and	Decrease in Chi-Square	New Estimate
Q17	Q15	10.1	0.33
Q17	Q16	12.3	0.37
Q18	Q16	9.0	0.30
Q18	Q17	17.8	0.53
Q22	Q17	8.1	0.28
Q22	Q18	11.5	0.32
Q23	Q22	11.0	0.34
Q24	Q18	9.4	0.25
Q25	Q16	9.8	0.37
Q25	Q17	45.1	0.99
Q25	Q18	30.8	0.78
Q25	Q22	15.1	0.42
Q25	Q23	24.4	0.77
Q26	Q23	16.0	-0.30
Q28	Q16	8.9	-0.20
Q28	Q25	10.4	-0.30
Q29	Q25	10.0	0.47
Q29	Q26	15.6	0.28
Q30	Q12	13.0	-0.33
Q30	Q17	34.7	0.77
Q30	Q18	13.3	0.45
Q30	Q25	41.1	0.92
Q31	Q22	16.6	-0.28
Q31	Q29	14.1	-0.36
Q32	Q16	8.3	0.24
Q32	Q17	16.5	0.43
Q32	Q18	9.5	0.31
Q32	Q25	8.2	0.34
Q33	Q17	17.5	-0.29
Q33	Q25	16.9	-0.32
Q33	Q30	10.9	-0.23
Q35	Q15	9.4	0.25
Q35	Q16	8.6	0.23
Q36	Q16	9.2	-0.22
Q36	Q23	9.3	-0.30
Q36	Q32	11.8	-0.26
Q37	Q16	9.9	0.32
Q38	Q17	8.1	-0.26
Q38	Q22	9.6	-0.21
Q38	Q25	12.0	-0.35
Q39	Q26	11.4	0.20
Q40	Q34	8.7	-0.22
Q41	Q17	9.7	0.41
Q41	Q25	19.3	0.64
Q41	Q30	14.3	0.48
Q42	Q17	21.3	0.58
Q42	Q18	7.9	0.34
Q42	Q25	32.2	0.79
Q42	Q27	11.8	0.44
Q42	Q30	9.0	0.37
Q42	Q33	11.8	-0.23
Q42	Q41	24.4	0.61
Q43	Q17	10.4	0.39
Q43	Q23	11.1	0.42
Q43	Q25	32.8	0.77
Q43	Q30	57.1	0.89
Q43	Q32	8.8	0.28
Q43	Q36	11.0	-0.28
Q43	Q41	12.0	0.41
Q43	Q42	10.4	0.37
Q44	Q15	14.3	-0.22
Q44	Q17	14.7	-0.29
Q44	Q25	25.1	-0.42
Q44	Q30	11.0	-0.24
Q44	Q32	10.4	-0.19
Q44	Q40	9.8	-0.21
Q44	Q41	12.2	-0.26
Q44	Q42	9.9	-0.22
Q44	Q43	16.3	-0.28
Q45	Q15	14.6	0.28
Q45	Q17	11.6	0.32
Q45	Q34	8.4	-0.18
Q46	Q18	7.9	-0.22
Q46	Q30	10.5	-0.27
Q46	Q31	9.2	0.18
Q46	Q33	9.8	0.14
Q46	Q34	12.1	0.19
Q46	Q35	11.3	-0.21
Q46	Q39	11.4	-0.24
Q46	Q41	13.4	-0.30
Q46	Q42	10.4	-0.25
Q46	Q44	30.0	0.26
Q47	Q16	8.1	0.20
Q47	Q27	9.5	-0.28

Q47	Q32	9.9	0.22
Q47	Q37	13.8	0.31
Q47	Q44	7.9	-0.14
Q48	Q17	11.3	-0.27
Q48	Q26	13.0	0.15
Q48	Q29	8.9	0.24
Q48	Q41	9.5	-0.24
Q49	Q16	25.3	0.43
Q49	Q17	19.4	0.48
Q49	Q18	13.9	0.38
Q49	Q22	11.0	0.26
Q49	Q25	29.1	0.65
Q49	Q32	22.2	0.40
Q49	Q35	8.7	0.24
Q49	Q38	10.7	-0.24
Q49	Q41	19.3	0.47
Q49	Q42	21.8	0.48
Q49	Q44	18.7	-0.26
Q49	Q46	27.1	-0.35
Q49	Q47	14.6	0.27
Q50	Q49	8.7	0.19
Q51	Q33	10.9	-0.19
Q51	Q50	14.3	-0.24
Q52	Q29	14.8	-0.33
Q52	Q30	12.4	-0.29
Q53	Q15	16.9	0.46
Q53	Q16	8.5	0.33
Q53	Q17	32.0	0.80
Q53	Q18	22.3	0.63
Q53	Q25	37.6	0.96
Q53	Q29	14.9	0.55
Q53	Q30	14.8	0.53
Q53	Q31	13.4	-0.37
Q53	Q32	27.7	0.59
Q53	Q33	10.0	-0.24
Q53	Q35	19.1	0.46
Q53	Q36	12.3	-0.35
Q53	Q40	10.2	0.39
Q53	Q41	24.9	0.70
Q53	Q42	18.0	0.57
Q53	Q43	14.5	0.49
Q53	Q44	23.8	-0.39
Q53	Q46	24.2	-0.44
Q53	Q49	38.1	0.71
Q54	Q17	11.0	0.33
Q54	Q25	10.4	0.36
Q54	Q38	12.8	-0.24
Q54	Q41	13.7	0.36
Q54	Q53	13.6	0.39
Q55	Q16	10.1	-0.22
Q55	Q17	34.3	-0.53
Q55	Q18	9.6	-0.26
Q55	Q25	23.3	-0.48
Q55	Q30	9.0	-0.26
Q55	Q32	13.7	-0.26
Q55	Q33	22.0	0.22
Q55	Q34	9.4	0.18
Q55	Q35	10.5	-0.22
Q55	Q38	18.6	0.26
Q55	Q41	16.3	-0.36
Q55	Q42	8.8	-0.25
Q55	Q44	23.3	0.25
Q55	Q49	9.1	-0.22
Q55	Q53	32.8	-0.55
Q55	Q54	12.9	-0.24

Time used 19.047 seconds

Appendix C: Factor Load Determination within Clusters Using CFA Technique

The CFA technique tests the factors associated with the intuitively developed lane changing clusters for factorial load determination. The CFA technique tests if the variables that define each cluster appear consistent with the hypothesized construct of the researcher and significant within the cluster.

For the CFA technique, the study uses LISREL software, which follows the following procedure (Bryant et al., 1999):

1- Use the input data to calculate the genuine correlation between the survey's questions.

2- Conducts the CFA clustering model hypothesized by user to estimate "what the observed correlations among the survey questions should have been". The software assumes the hypothesized model by user is accurate.

3- Determines the difference between the observed correlations and the correlation in the model hypothesized by the user.

4- Finally, the software generates a maximum-likelihood chi-square value (calculating p-value) to investigate if the differences between observed correlations and hypothesized correlations have occurred by chance. Here, the software assumes the model is correct.

These steps indicate the goodness of fit in the hypothesized model (see Figure C-1)

In this study, authors identify four lane changing factor clusters: Safety, Temporal, Environmental, and Emotional. The CFA analysis indicates that the factors in each cluster significantly represent that cluster because none of the connections in Figure C-1 appear insignificant (red). Figure C-1 shows the path diagram of the software. The Root Mean Square Error Approximation (RMSEA) of the model also is 0.117; however, a RMSEA value lower than 0.1 typically indicates a better goodness of fit for a model. This indicates that some of the clusters may either be too large or contain factors do not match the overall cluster particularly well (indicated in red in Table C-1). The CFA model can be improved by removing less correlated factors from the clusters to capture an improved RMSEA; however, this paper seeks to place all potential factors identified by the focus groups within a cluster rather than develop a better fit. The investigation of finding the best fit CFA model is left for future study.

CFA also provides the factors' load, which identifies the strength of correlation with the other factors within each cluster, as well as the correlation of clusters with each other. Moreover, the correlation of the safety and environmental clusters is 94% based on CFA analysis output. This result indicates that majority of people who have safety concerns in discretionary lane changing, would also change lanes because of environmental factors. Table C-1 shows the factors' load in the different clusters, and Table C-2 shows the correlation of clusters with each other.

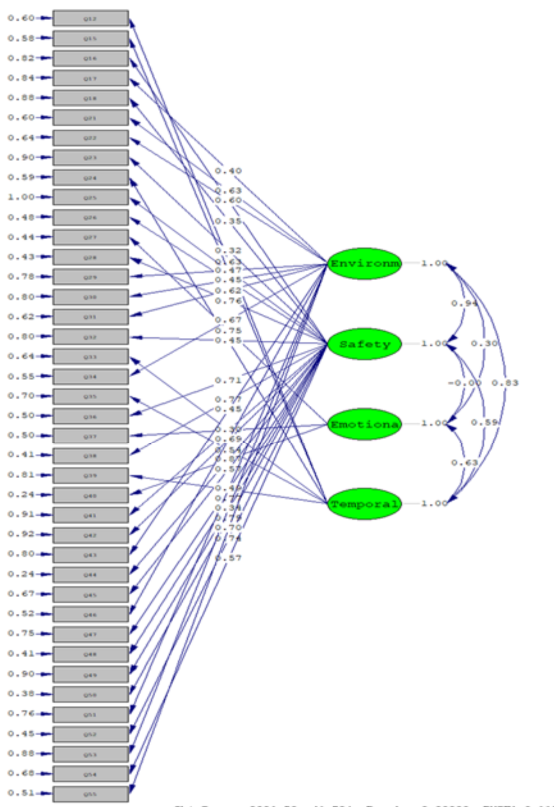


Figure C-0-1. Path Diagram of CFA Analysis

CFA Analysis Discussion

The most important outcome of the CFA analysis indicates that all factors remain significant (see Figure C-1; none of the factor connections appear in red). Table C-1 illustrates the factors' load of variables in different clusters for showing the importance and significance of each factor within their clusters. A larger factor load means that factor has a higher correlation with the other factors within the cluster. Therefore, a larger factor load also describes a factor's ability to represent the other factors within the cluster or the overall cluster. The safety cluster contains the most factors (19). In this cluster, the "*object in your lane (e.g. seeing a dead animal or a piece of lumber)*" and "*avoid a hazard such as fire along one side of a road*" have the highest factor loads, which mean these factors represent the safety cluster more effectively. The "*sleepy (e.g. in the morning when you go to work and you are sleepy)*" and "*truck or a heavy vehicle is beside you in the adjacent lane*" have the lowest factor load in the safety cluster. The highest factor loads can be used to calibrate safety-based discretionary lane changes in general while the lower factor loads may be dropped from this cluster to obtain a better goodness of fit.

In representing the environmental cluster with twelve factors, the "*lane blockage (e.g. stalled car in your lane)*" has the best measurement of this cluster and the "*other people in your car ask you to do*" is the least correlated factor with the rest of the environmental cluster. Observations on the current driving environment appear to provide the guiding motivation for this cluster as indicated by the strongest factor. The least important factors could be dropped to increase the goodness-of-fit for the CFA model.

Six factors appear in the temporal cluster. The "*in a rush; I need to be someplace soon (e.g. in the morning for going to work)*" has the highest correlation with the temporal cluster and "*Congestion downstream in your lane (Lane Density matters)*" has the lowest relationship with this cluster. The role of time as dictated by the strongest factor provides a strong motivation for this type of discretionary lane change.

Finally, the emotional cluster has three representative factors, and all these factors represent this cluster very well. Based on LISREL software output (appendix B), all the emotional factors which are "*any kind of distraction (Listening to the radio, using GPS, seeing billboards, talking on the phone, someone is talking to you, etc.)*", "*newer car or smaller and more flexible car. (Type or model of the car matters)*" and "*good mood (e.g. listening to a music or being excited)*" have a higher R square in comparison with other factors which means they are well correlated together, which may be impacted by the small number of factors in the cluster.

See Appendix B for the LISREL output for the factors' load and R square of each factor.

Table C-1. Factors' Load within Clusters

Cluster	Factor ID	Factors' Load within Each Cluster
Temporal	12	0.75
	15	0.88
	24	0.71
	33	0.54
	35	0.66
	39	0.56
Safety	16	0.52
	18	0.49
	23	0.49
	25	0.09
	26	0.76
	28	0.98
	32	0.56
	36	0.96
	38	1.1
	41	0.43
	42	0.38
	44	1.28
	45	0.69
	47	0.53
	48	0.96
	49	0.39
	50	1.03
	52	0.97
	54	0.71
Environ ment	17	0.61
	21	0.88

	22	0.76
	29	0.74
	30	0.69
	31	0.76
	34	0.8
	43	0.63
	46	0.83
	51	0.62
	53	0.55
	55	0.91
Emotional	27	1.47
	37	1.26
	40	1.62

Another important piece of CFA analysis is to obtain the correlations of the clusters. As shown in Table C-2, the safety and environmental clusters have 94% correlation, which represents the strongest relationship between clusters. This correlation indicates that the importance of safety factors when changing lanes provides a strong indicator of the importance of the environmental factors. The emotional and safety clusters have no correlation, which means the importance of the safety cluster and its factors provides no indication of the importance of the emotional cluster and its factors. Table 2-6 shows the correlations between the clusters.

Table C-2. Cluster Correlation Matrix

Clusters	Environmental	Safety	Emotional	Temporal
Environmental	1			
Safety	0.94	1		
Emotional	0.3	0	1	
Temporal	0.83	0.59	0.63	1

Importance of Clusters in Lane Changing Behavior

This study seeks to determine the importance of clusters in triggering lane changing events. The authors aim to identify the most important clusters by calculating the mean value of each cluster for each individual (∑ *Scores of Cluster's Factors/Number of Cluster's Factors*) and the overall cluster ∑ *Subjects' Scores in Each Cluster / 220*). Table C-3 shows a sample of the clusters' score for the first three subjects and the mean of each cluster.

Table C-3. Sample of Clusters' Scores for Subjects

Participants	Environmental	Safety	Temporal	Emotional
Subject 1	3.8	3.2	2.5	5.7
Subject 2	1.7	1.8	1.7	2.3
Subject 3	3.0	2.7	3.0	2.7
. .				
Mean of Clusters	2.8	2.5	3	4

Since a score of 1 is associated to "Strongly Agree" for changing lane and a score of 7 is associated to "Strongly Disagree" for changing lane, a lower cluster mean shows a greater importance. Therefore, the safety category represents the most important cluster followed by the environmental category. Temporal factors appear to play an important role in lane changing decisions, too. Lastly, the emotional cluster exhibits an inconsistent impact on the lane changing event and only correlates with the temporal cluster.

Comparisons of Lane Changing Clusters

The final analyses compare the defined lane changing clusters to determine if the clusters appear significantly different from each other. The outcome of this analysis indicates that people change lanes due to multiple reasons. To compare the clusters for obtaining their significance on lane changing, first the normality of data distribution for each cluster should be calculated. Four different normality tests (Shapiro-Wilk, Anderson-Darling, Lilliefors and Jarque-Bera tests) were conducted on each cluster to assure the robustness of normality tests' results. The normality test interpretation is as follows:

H_0: The variable from which the sample was extracted follows a Normal distribution.

H_a: The variable from which the sample was extracted does not follow a Normal distribution.

The assumed significance level is 0.05, so if the p-value of normality tests are less than 0.05, the H_0 is rejected. Based on these normality tests, the data distribution of all clusters except environmental are not normal. Therefore, the authors conducted the non-parametric Kruskal-Wallis to investigate if the surveys' responses are significantly different within the defined clusters. Table C-4 summarizes the normality tests on different lane changing clusters.

Table C-4. Summary of Normality Tests Results

Variable\Test	Shapiro-Wilk	Anderson-Darling	Lilliefors	Jarque-Bera
Emotional	0.002	0.013	0.004	0.146
Temporal	0.040	0.038	0.009	0.665
Safety	0.000	< 0.0001	< 0.0001	< 0.0001
Environmental	0.114	0.161	0.075	0.715

Kruskal-Wallish Test

The Kruskal-Wallish is a non-parametric statistical test (used when the data set does not have a normal distribution) is used to compare two or more independent samples to investigate if the samples come from the same distribution or not. The test interpretation is as follows:

H_0: The samples come from the same population.

H_a: The samples do not come from the same population.

Based on outcome of Kruskal-Wallish test shown in Table C-5, the p-value is <0.0001 (less than significance level=0.05), which reveals that the responses distributions of clusters appear significantly different (reject H_0 and accept H_a). This result indicates that the different lane changing clusters matter to respondents and their responses to different lane changing factors remain varied.

Table C-5. Kruskal-Wallish Test Output

K (Observed value)	144.919
K (Critical value)	7.815
DF	3
p-value (one-tailed)	< 0.0001

alpha	0.05

Multiple Pairwise Comparisons Using Dunn's procedure

This comparison seeks to determine if a cluster appears significantly more important than other clusters using Dunn’s procedure. The Dunn’s statistical hypothesis test interpretation is as follows:

H_0: There is no difference between two clusters.

H_a: There is a difference between two clusters.

Based on the results of Dunn’s test shown in Table C-6, all p-values of Dunn’s test are less than 0.05 (significance level) except the temporal and environmental comparison test. Therefore, H_0 is rejected and the H_a is accepted. This result indicates that (1) discretionary lane changing depends on numerous situations and (2) some motives (i.e. safety) appear significantly more important than others for causing discretionary lane changing. Therefore, people change lanes due to multiple different reasons which can be clustered in different categories. The safety cluster appears significantly more important than all other clusters, and the temporal and environmental clusters appear significantly more important than the emotional cluster.

Table C-6. Summary Outputs of Dunn’s Tests for Multiple Pairwise Comparisons

Pairwise comparisons				
Differences				
Clusters	Environmental	Safety	Temporal	Emotional
Environmental	0			
Safety	**-75.714**	0		
Temporal	44.652	**120.366**	0	
Emotional	**206.025**	**281.739**	**161.373**	0
p-values				
Cluster	Environmental	Safety	Temporal	Emotional
Environmental	1			
Safety	**0.002**	1		
Temporal	0.065	**< 0.0001**	1	
Emotional	**< 0.0001**	**< 0.0001**	**< 0.0001**	1

Significant Differences				
Clusters	Environmental	Safety	Temporal	Emotional
Environmental	No			
Safety	**Yes**	No		
Temporal	No	**Yes**	No	
Emotional	**Yes**	**Yes**	**Yes**	No

Appendix D: Normality Tests of Lane Changing Clusters

1-Emotional Cluster

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Emotional	220	0	220	1.000	7.000	3.977	1.524

Shapiro-Wilk test (Emotional):

W	0.979
p-value (Two-tailed)	0.002
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.

The risk to reject the null hypothesis H0 while it is true is lower than 0.23%.

Anderson-Darling test (Emotional):

A^2	0.984
p-value (Two-tailed)	0.013
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.

The risk to reject the null hypothesis H0 while it is true is lower than 1.32%.

Lilliefors test (Emotional):

D	0.076
D (standardized)	1.125
p-value (Two-tailed)	0.004
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.37%.

Jarque-Bera test (Emotional):

JB (Observed value)	3.842
JB (Critical value)	5.991
DF	2
p-value (Two-tailed)	0.146
alpha	0.05

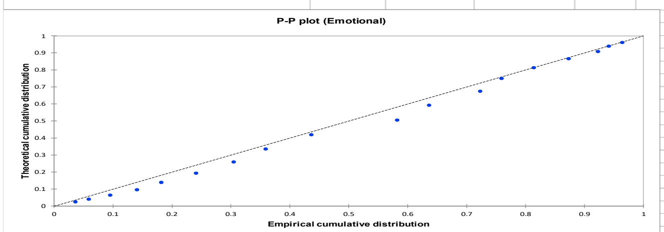
Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.

The risk to reject the null hypothesis H0 while it is true is 14.65%.

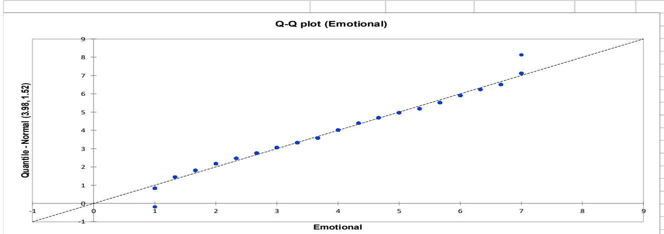
Summary:

Variable\Test	Shapiro-Wilk	Anderson-Darlin	Lilliefors	arque-Bera
Emotional	**0.002**	**0.013**	**0.004**	0.146

Normal P-P plots:



Normal Q-Q plots:



2- Temporal Cluster

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Temporal	220	0	220	1.000	5.833	2.985	0.958

Shapiro-Wilk test (Temporal):

W	0.987
p-value (Two-tailed)	0.040
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 4.01%.

Anderson-Darling test (Temporal):

A²	0.800
p-value (Two-tailed)	0.038
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 3.78%.

Lilliefors test (Temporal):

D	0.071
D (standardized)	1.051
p-value (Two-tailed)	0.009
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.94%.

Jarque-Bera test (Temporal):

JB (Observed value)	0.815
JB (Critical value)	5.991
DF	2
p-value (Two-tailed)	0.665
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.

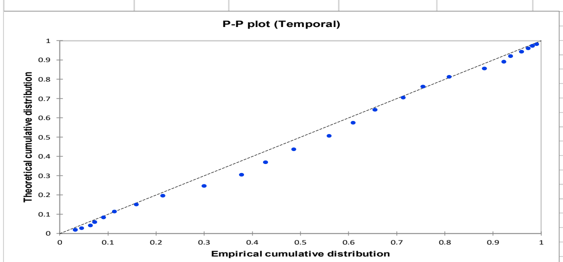
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.

The risk to reject the null hypothesis H0 while it is true is 66.52%.

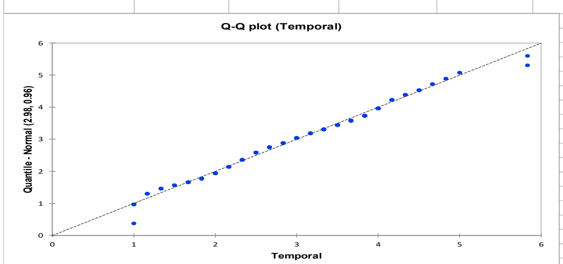
Summary:

Variable\Test	Shapiro-Wilk	Anderson-Darling	Lilliefors	Jarque-Bera
Temporal	**0.040**	**0.038**	**0.009**	0.665

Normal P-P plots:



Normal Q-Q plots:



3- Safety Cluster

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Safety	220	0	220	1.000	5.211	2.534	0.772

Shapiro-Wilk test (Safety):

W	0.970
p-value (Two-tailed)	0.000
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.

Anderson-Darling test (Safety):

A^2	1.862
p-value (Two-tailed)	< 0.0001
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.

Lilliefors test (Safety):

D	0.104
D (standardized)	1.544
p-value (Two-tailed)	< 0.0001
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.

Jarque-Bera test (Safety):

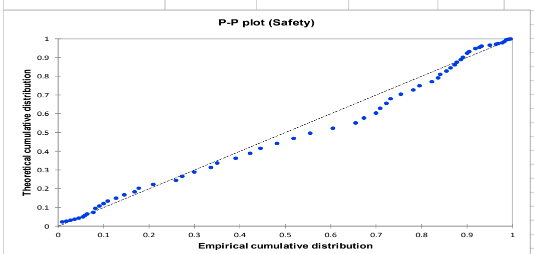
JB (Observed value)	18.475
JB (Critical value)	5.991
DF	2
p-value (Two-tailed)	< 0.0001
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.

Summary:

Variable\Test	Shapiro-Wilk	nderson-Darlin	Lilliefors	arque-Bera
Safety	**0.000**	**< 0.0001**	**< 0.0001**	**< 0.0001**

Normal P-P plots:



Normal Q-Q plots:

4- Environmental Cluster

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Environmental	220	0	220	1.000	5.333	2.793	0.866

Shapiro-Wilk test (Environmental):

W	0.990
p-value (Two-tailed)	0.114
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.

As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.

The risk to reject the null hypothesis H0 while it is true is 11.43%.

Anderson-Darling test (Environmental):

A^2	0.543
p-value (Two-tailed)	0.161
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.

As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.

The risk to reject the null hypothesis H0 while it is true is 16.13%.

Lilliefors test (Environmental):

D	0.057
D (standardized)	0.851
p-value (Two-tailed)	0.075
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.

As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.

The risk to reject the null hypothesis H0 while it is true is 7.55%.

Jarque-Bera test (Environmental):

JB (Observed value)	0.671
JB (Critical value)	5.991
DF	2
p-value (Two-tailed)	0.715
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.

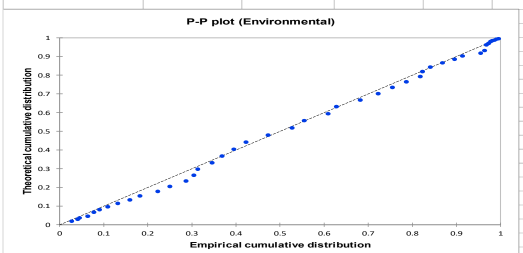
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.

The risk to reject the null hypothesis H0 while it is true is 71.50%.

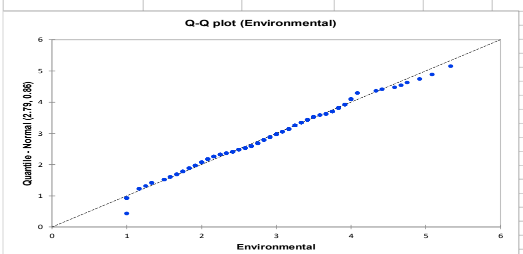
Summary:

Variable\Test	Shapiro-Wilk	nderson-Darlin	Lilliefors	arque-Bera
Environmental	0.114	0.161	0.075	0.715

Normal P-P plots:



Normal Q-Q plots:



Appendix E: Sample of z-score calculation and table of all z-scores

For instance, the first participant chose agree to change lane for factor ID of 12, so the score of this response is 6 and:

z-score: (6-Average scores of first participant response)/ Standard deviation scores of first participant responses)= (6-5.73/1.085)= 0.253

Next page shows the table of all z-scores based on above calculation.

Table E-1: z-scores

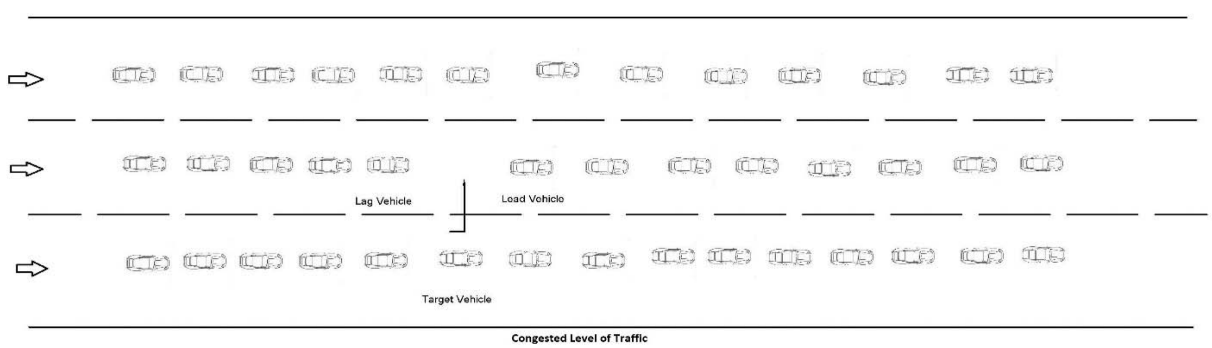
Q12	Q15	Q16	Q17	Q18	Q21	Q22	Q23	Q24	Q25	Q26	Q27	Q28	Q29	Q30	Q31	Q32	Q33	Q34	Q35	Q36	Q37	Q38	Q39	Q40	Q41	Q42	Q43	Q44	Q45	Q46	Q47	Q48	Q49	Q50	Q51	Q52	Q53	Q54	Q55
0.253282	0.253282	0.253282	-0.66774	0.253282	1.174307	-1.58877	-1.58877	-1.58877	1.174307	-0.66774	1.174307	1.174307	0.253282	-1.58877	0.253282	-0.66774	0.253282	1.174307	-1.58877	0.253282	-1.58877	1.174307	1.174307	0.253282	-0.66774	0.253282	-1.58877	0.253282	1.174307	-0.66774	1.174307	0.253282	0.253282	-0.66774	-1.58877	1.174307	0.253282	0.253282	1.174307
0.89913	-1.4212	-1.4212	0.89913	-0.26104	0.89913	-0.26104	0.89913	-0.26104	0.89913	-1.4212	-0.26104	-0.26104	-0.26104	0.89913	-0.26104	-0.26104	-0.26104	-0.26104	0.89913	0.89913	0.89913	0.89913	0.89913	-2.58137	0.89913	-2.58137	0.89913	0.89913	0.89913	0.89913	0.89913	-0.26104	-0.26104	-0.26104	-0.26104	0.89913	-1.4212	-1.4212	-0.26104
1.561249	0.520416	1.561249	-0.52042	-0.52042	0.520416	-0.52042	-1.56125	-0.52042	-0.52042	1.561249	-0.52042	0.520416	1.561249	-0.52042	-1.56125	-0.52042	-1.56125	0.520416	1.561249	-0.52042	0.520416	1.561249	-0.52042	1.561249	0.520416	0.520416	0.520416	-0.52042	0.520416	-0.52042	-0.52042	1.561249	-1.56125	-0.52042	-0.52042	-0.52042	-0.52042	-1.56125	-0.52042
-0.37991	-0.37991	-1.46539	0.705556	1.791027	-0.37991	0.705556	-1.46539	0.705556	-0.37991	-0.37991	0.705556	0.705556	0.705556	-0.37991	0.705556	0.705556	-1.46539	-0.37991	-1.46539	1.791027	-0.37991	0.705556	-0.37991	-1.46539	-1.46539	-1.46539	-0.37991	0.705556	-0.37991	0.705556	1.791027	1.791027	0.705556	-0.37991	-1.46539	0.705556	-0.37991	-0.37991	0.705556
0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	-2.37509	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	-2.37509	0.263899	0.263899	0.263899	0.263899	-5.01409	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899	0.263899
0.806226	-1.20934	-1.20934	-1.20934	0.806226	0.806226	0.806226	0.806226	0.806226	0.806226	-1.20934	-1.20934	0.806226	0.806226	-1.20934	0.806226	-1.20934	0.806226	-1.20934	-1.20934	0.806226	0.806226	0.806226	0.806226	-1.20934	-1.20934	0.806226	-1.20934	-1.20934	0.806226	0.806226	0.806226	0.806226	0.806226	-1.20934	0.806226	0.806226	-1.20934	0.806226	-1.20934
2.476442	0.904098	-0.66825	-0.66825	-0.66825	0.904098	-0.66825	-0.66825	-0.66825	0.904098	-0.66825	0.904098	0.904098	0.904098	0.904098	-0.66825	-0.66825	-0.66825	-0.66825	-0.66825	2.476442	0.904098	-0.66825	-0.66825	-0.66825	-0.66825	-0.66825	2.476442	-0.66825	0.904098	0.904098	-0.66825	-0.66825	-0.66825	0.904098	-0.66825	-0.66825	-0.66825	-0.66825	-0.66825
0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	-2.16421	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	-2.16421	0.309173	0.309173	0.309173	-2.16421	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	0.309173	-4.6376	0.309173	0.309173
0.809228	0.809228	0.809228	0.809228	-1.34871	-0.26974	-0.26974	-1.34871	-1.34871	1.8882	-0.26974	-0.26974	-1.34871	1.8882	0.809228	-0.26974	0.809228	-0.26974	0.809228	0.809228	-1.34871	-1.34871	-0.26974	-0.26974	-0.26974	-0.26974	1.8882	-0.26974	-1.34871	0.809228	-0.26974	0.809228	0.809228	-0.26974	-0.26974	1.8882	-0.26974	-1.34871	-1.34871	-0.26974
0.454773	0.454773	0.454773	0.454773	0.454773	-2.14393	0.454773	-2.14393	-2.14393	-2.14393	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	-2.14393	0.454773	0.454773	0.454773	0.454773	-2.14393	-2.14393	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773	0.454773
0.242353	0.242353	0.242353	-1.69647	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	-1.69647	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	-5.57412	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353	0.242353
-1.73889	1.242063	0.248413	1.242063	1.242063	-0.74524	-0.74524	-0.74524	0.248413	-1.73889	0.248413	0.248413	0.248413	1.242063	-1.73889	1.242063	1.242063	0.248413	1.242063	-0.74524	-0.74524	-0.74524	1.242063	1.242063	1.242063	0.248413	1.242063	0.248413	-0.74524	0.248413	-1.73889	-0.74524	0.248413	-0.74524	-0.74524	-0.74524	1.242063	-0.74524	-0.74524	-0.74524
-1.83258	-1.83258	-1.83258	0.532038	0.532038	-1.83258	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	-1.83258	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	0.532038	-1.83258	0.532038	0.532038	0.532038	0.532038	-1.83258	0.532038	-1.83258	-1.83258	0.532038	0.532038	0.532038
0	1.331438	-1.33144	1.331438	1.331438	-1.33144	0	1.331438	-1.33144	0	0	0	0	0	0	0	-1.33144	-1.33144	1.331438	1.331438	1.331438	1.331438	1.331438	-1.33144	0	0	0	0	0	0	-1.33144	1.331438	1.331438	0	0	-1.33144	-1.33144	-1.33144	0	-1.33144
0.114631	1.031675	0.114631	0.114631	0.114631	1.031675	1.031675	0.114631	-1.71946	-1.71946	1.031675	-1.71946	1.031675	1.031675	-1.71946	-0.80241	0.114631	1.031675	1.031675	-1.71946	1.031675	1.031675	0.114631	-1.71946	-0.80241	0.114631	-0.80241	0.114631	1.031675	0.114631	1.031675	0.114631	-0.80241	-1.71946	1.031675	0.114631	0.114631	0.114631	-0.80241	1.031675
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Appendix F: Surveys Questions of Actions of Vehicles In Lane Changing Scenarios

Congested-Discretionary Situation

Each lane changing behavior depends on interaction with other vehicles around you. Questions below are related to the role of each vehicle in lane changing process:

Figure below shows the main vehicles that are in lane changing process. Imagine you are on **congested traffic level**, then based on this picture please answer the following questions:



- Imagine you are the lag vehicle, what will be your action during lane changing process
  - Yield for target vehicle
  - Accelerate in order to prevent lane changing process happen
  - Keep your speed
  - Also you may change lane

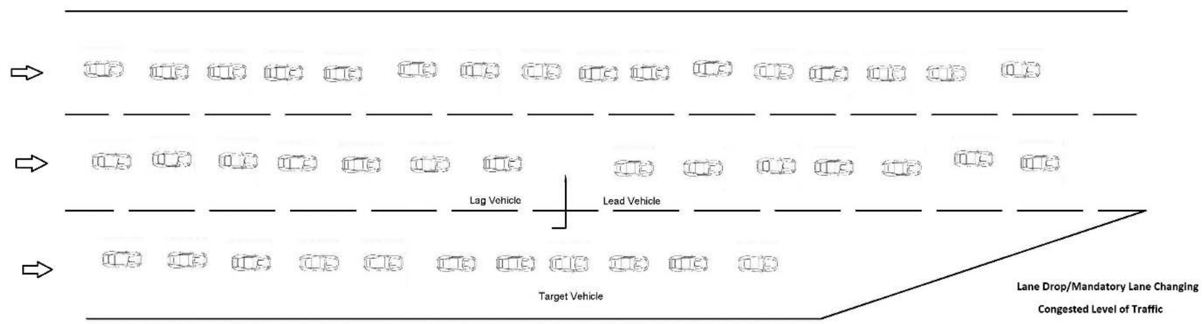
- Imagine you are the target vehicle, what will be your action during lane changing process
  - Change lane aggressively without checking whether acceptable gap exist or not
  - Waiting for an acceptable gap, then change lane

- Imagine you are the lead vehicle, what will be your action during lane changing process
  - Accelerate in order to help target vehicle to come to your lane
  - Decelerate in order to prevent lane changing happen
  - Keep your speed
  - Change lane
  - You do not care about what happens behind you

Congested-Merging Situation

Each lane changing behavior depends on interaction with other vehicles around you. Questions below are related to the role of each vehicle in lane changing process:

Now consider you are on **lane drop/merging lane changing in a congested level of traffic situation**, then answer the following questions:



- Imagine you are the lag vehicle, what will be your action during lane changing process
  - Yield for target vehicle
  - Accelerate in order to prevent lane changing process happen
  - Keep your speed
  - Also you may change lane

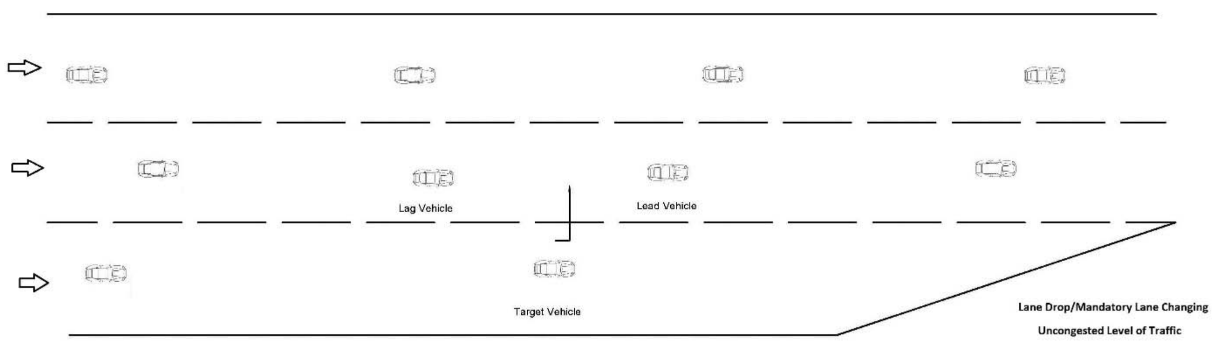
- Imagine you are the target vehicle, what will be your action during lane changing process
  - Change lane aggressively without checking whether acceptable gap exist or not
  - Waiting for an acceptable gap, then change lane

- Imagine you are the lead vehicle, what will be your action during lane changing process
  - Accelerate in order to help target vehicle to come to your lane
  - Decelerate in order to prevent lane changing happen
  - Keep your speed
  - Change lane
  - You do not care about what happens behind you

Uncongested-Merging Situation

Each lane changing behavior depends on interaction with other vehicles around you. Questions below are related to the role of each vehicle in lane changing process:

Now consider you are on **lane drop/merging lane changing in an uncongested level of traffic situation**, then answer the following questions:



- Imagine you are the lag vehicle, what will be your action during lane changing process
  - Yield for target vehicle
  - Accelerate in order to prevent lane changing process happen
  - Keep your speed
  - Also you may change lane

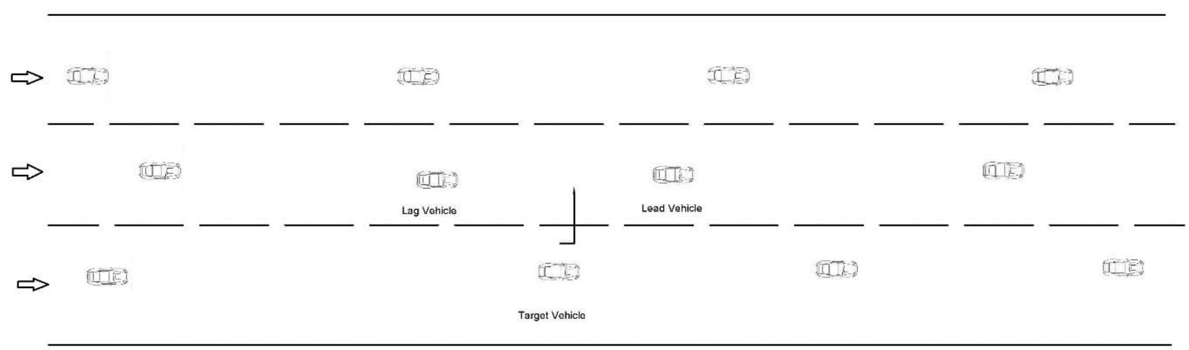
- Imagine you are the target vehicle, what will be your action during lane changing process
  - Change lane aggressively without checking whether acceptable gap exist or not
  - Waiting for an acceptable gap, then change lane

- Imagine you are the lead vehicle, what will be your action during lane changing process
  - Accelerate in order to help target vehicle to come to your lane
  - Decelerate in order to prevent lane changing happen
  - Keep your speed
  - Change lane
  - You do not care about what happens behind you

Uncongested-Discretionary Situation

Each lane changing behavior depends on interaction with other vehicles around you. Questions below are related to the role of each vehicle in lane changing process:

Now imagine you are on **uncongested traffic level**. Based on this assumption and the picture below answer the following questions:



- Imagine you are the lag vehicle, what will be your action during lane changing process
  - Yield for target vehicle
  - Accelerate in order to prevent lane changing process happen
  - Keep your speed
  - Also you may change lane
- Imagine you are the target vehicle, what will be your action during lane changing process
  - Change lane aggressively without checking whether acceptable gap exist or not
  - Waiting for an acceptable gap, then change lane
- Imagine you are the lead vehicle, what will be your action during lane changing process
  - Accelerate in order to help target vehicle to come to your lane
  - Decelerate in order to prevent lane changing happen
  - Keep your speed
  - Change lane
  - You do not care about what happens behind you

Appendix G: Explanation of collecting real-world data

- When the target vehicle changes lane with constant speed or increase his/her speed the action of target vehicle is considered as “changing lane”,
- When the target vehicle decreases or wait till the adjacent vehicle passes them the action of target vehicle is considered as “waiting for an acceptable gap”.
- The actions of drivers as lag vehicles are easy to capture. The subjects as lag vehicle might accelerate, decelerate, keep current speed or change lane when their front vehicle attempts to enter to their lane.
- The behavior of front vehicle of subject vehicle is collected as lead vehicle’s actions. If the front vehicle brakes, the action of decelerating is captured.
- If the front vehicle maintain the distance with the subject vehicle or increase that distance, the lead vehicle actions are recorded as keeping current speed and accelerating respectively.
- The front vehicle also might change lane.

Hypotheses about how behaviors will differ across the dimensions for the different roles

- As the target vehicle, in merging scenario drivers would change lane more aggressively and the time spent in the current lane is critical for them, since they cannot stay in that lane forever. However, in discretionary lane changing, target vehicle mostly change lane in order to gain speed and or be in a better condition, so speed differences as well as lane density differences of current lane and the target lane are critical.
- As the lag vehicle, in congested situations, people may be more cooperative since the speed is low and the lost time is minimal in cooperation. However, in uncongested situation, people may prefer to maintain their speed in order to minimize speed variation.
- As the lead vehicle, people may mostly keep their current speed, but the cooperation might be seen more often in uncongested situation because they would have enough space to accelerate.

Appendix H: A sample of calculation (for lag vehicle) for obtaining the confidence intervals of actions

For proportions ⇒ mean = $\sqrt{\frac{P(1-P)}{n}}$ where p is proportion

Confidence interval = p $\pm$ z * mean where z is 1.96 with the confidence of 95%

⇒ Confidence interval = p $\pm$ 1.96* $\sqrt{\frac{P(1-P)}{n}}$

For example: Lag vehicle has four actions

p (Action 1)= 0.48

p (Action 2)= 0.14

p (Action 3)= 0.21

p (Action 4)= 0.17

Confidence interval of Action 1= $0.48 \pm 1.96 * \sqrt{\frac{0.48(1-0{\cdot}48)}{275}}$

$$0.48+1.96 * \sqrt{\frac{0.48(1-0{\cdot}48)}{275}}=0.54$$

$$0.48-1.96 * \sqrt{\frac{0.48(1-0{\cdot}48)}{275}}=0.42$$

Confidence interval of Action 1=(0.42, 0.54) ⇒ Interval=0.12

Confidence interval of Action 2=(0.1, 0.18) ⇒ Interval=0.08

Confidence interval of Action 3=(0.16, 0.26) ⇒ Interval=0.1

Confidence interval of Action 4=(0.13, 0.21) ⇒ Interval=0.07

Since the first action has the largest interval distance, this action is determined as the critical action for lag vehicle role.