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Determinants Behind the Taste Variation in Discretionary Lane Changing Behavior of Drivers Facing Downstream Queues

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ABSTRACT: Lane-changing behavior can significantly affect many aspects of traffic flow including capacity, shock waves, and safety. Therefore, it is imperative to understand the determinants behind lane change behavior. This paper investigates the determinants of lane-changing in congested traffic using video-recording as well as a survey approach. A mixed logit model was estimated to account for unobserved heterogeneity in lane-changing behavior across drivers. Estimation results show that all categories of explanatory variables including socioeconomic, driving style, and road environment have a significant effect on lane changing behavior. Besides, unobserved heterogeneity and taste variation among drivers with regards to the lateral distance of the target vehicle from the left car has been observed. Among the non-random parameters, speed of target vehicle, being a law-evading driver, disregarding yellow traffic signals at intersections, lateral distance of target vehicle from right/left cars, and experiencing at least two accidents are positively associated with a higher likelihood of lane changing when a driver encounters a downstream queue. The aforementioned interesting findings can significantly help to improve the performance of traffic flow models for the purpose of replicating and predicting traffic flow.

KEYWORDS: Discretionary Lane Changing; Mixed Logit Model; Taste Variation; Congestion; Heterogenous Drivers

1. INTRODUCTION AND BACKGROUND

On highways, the motion of vehicles can be categorized into longitudinal and lateral movements (Wei et al., 2019). Car-following is when two vehicles travel longitudinally in the same lane while one vehicle is ahead (the preceding vehicle) and one is behind (the following vehicle) (Zhu et al., 2016). Lane changing (LC), however, refers to lateral movements that are always accompanied by longitudinal movements (Balal et al., 2014). Research on car-following has been conducted for more than 50 years, however, LC received less attention in comparison with car-following models. There are two possible explanations for this issue: (I) lane changes involve two-dimensional motions, and (II) lane changes involve a greater number of vehicles (Ma & Li, 2023). Lane changes can be classified as either mandatory or discretionary (Li et al., 2021). When a vehicle is attempting to make a right turn at an intersection or exit a freeway, lane changes are usually required as it moves from the left or center lane to the rightmost lane (Ali et al., 2020). Discretionary lane changes, on the other hand, occur when a driver is following another vehicle with a lower speed than the driver's preferred speed and moves to the adjacent lane in order to speed up (Schmidt et al., 2021; Zhang et al., 2024).

There are many aspects of traffic flow that are affected by LC behavior. For example, a lane change that has been conducted improperly leads to a decrease in traffic flow characteristics as well as an increase in traffic safety concerns. LC is one of the most common causes of motor vehicle crashes in the United States. According to official statistics, a third of all road crashes occur when vehicles change lanes or veer off the road (Guo et al., 2018). Furthermore, statistics indicate that sudden lane changes accounted for 17.0 % of all serious accidents in Middle Eastern countries between 2010 and 2017, while speeding accounted for 12.8 % (Jamal et al., 2020). The LC can also significantly influence traffic breakdowns or capacity drops (Cassidy & Rudjanakanoknad, 2005; Jin, 2013), traffic oscillations (Zheng et al., 2011), relaxations (Laval & Leclercq, 2008; Lecle rcq et al., 2007), and moving bottlenecks (Laval & Daganzo, 2006). Therefore, the need for further research on driver behavior and decisions regarding LC is imperative and necessary.

Although many LC models have been developed, the literature is less comprehensive than the car-following literature. Based on the prior studies which will be discussed as follows, there are a variety of factors affecting LC behavior. An analytical hierarchy process (AHP) coupled with the best-worst method (BWM) was used by Farooq et al. (2021) to assess and prioritize the significant factors affecting frequent lane changes. They found that traffic characteristics, followed by human factors and road characteristics, were the major factors contributing to frequent lane changes. Moreover, Zheng et al. (2014) found that driver's decisions to change lanes is extremely complicated and are affected by traffic, individuals including socioeconomic and driving attitude, and road characteristics (Sun & Elefteriadou, 2010, 2012). In order to study the impact of traffic characteristics, the majority of prior studies developed macroscopic and microscopic models. Traffic density, traffic flow rate, and space mean speed are calculated by macroscopic models which treat vehicles as a fluid stream. This approach was used by Knoop et al. (2012) to determine that density values between the current lane and the target lane affected the likelihood of discretionary lane changes. Similarly, Mullakkal-Babu et al. (2020) found that the number of lane changes increases with the density in the origin lane for a fixed density in the target lane. Surprisingly, Toth et al. (2015) acknowledged that it also increases with the density in the target lane for a fixed density in the origin lane. Tang et al. (2009) understood that the relationship between the number of lane changes and target lane speed is parabolic. As a macroscopic approach, kinematic wave theory has been deployed to study LC behavior (Daganzo, 2002; Jin, 2010). The relationships between microscopic vehicle features and LC were explored using microscopic models, as a complementary approach to these macroscopic models. Numerous microscopic studies have delved into the intricacies of LC behavior. These investigations specifically focus on how drivers respond to acceptance gaps, with lane changes occurring when such gaps are assured. There have been a number of studies conducted to attempt to determine the reasonable range for acceptance gaps that will influence the likelihood of LC (Bagheri et al., 2023; Farah et al., 2009; Zhang, 2004).

In contrast to macroscopic and microscopic approaches, Econometrics models have been used in a limited number of studies (Park et al., 2015; Lee et al., 2016; Toledo et al., 2009; Alshehri and Abdul Aziz, 2022), however, it is possible to consider a wider range of factors. For instance, using a logistic regression model, Park et al. (2015) determined that differences in speed and density between adjacent lanes significantly affected LC probabilities. Using an exponential probability model, the likelihood of LC behavior has been predicted as a function of differences in lane speeds and lead gaps by Lee et al. (2016). A probabilistic lane change model has been developed by Toledo et al. (2009) based on utility theory. Their model considered both mandatory and discretionary lane changes concurrently. Investigations into LC decisions have taken into account various factors, including gap sizes, vehicle speed, proximity to the intended exit off-ramp, and avoidance of the nearest lane to the shoulder, as well as individual driving styles and capabilities. Using the focus group method, Sun and Elefteriadou (2010) investigated the types of drivers, the probability of making discretionary lane changes, and the factors affecting the execution of discretionary lane changes. In another study by Sun and Elefteriadou (2012), using an in-vehicle experiment, probability functions for individual LC scenarios were formulated, integrating driver-specific characteristics that prior models often overlooked. Alshehri and Abdul Aziz (2022) employed a logistic stepwise selection procedure to examine the influence of vehicle attributes (such as length and width) and flow characteristics (including headways and lead-lag gaps) on the decision-making process related to LC. The factors associated with an increased likelihood of discretionary lane changes include the spacing between vehicles (referred to as space headway) within the original lane, the distance between the subject vehicle and the vehicle in the target lane (known as the lead gap), and the vehicle class (whether it is an automobile or a truck). A mathematical analysis of driver characteristics and traffic environments was conducted by Ma et al. (2020) to determine how frequently drivers changed lanes. There was a strong correlation between frequent lane changes and traffic environment, small cars, and density of traffic flow. A common LC behavior observed during aggressive driving was caused primarily by drivers. Individuals exhibiting a propensity for frequent lane-changing behavior were predominantly male, aged between 31 and 40 years, and possessed lower academic qualifications as well as they tended to display choleric personality traits. Driver behavior during mandatory and discretionary lane changes was compared by Vechione et al. (2018). They examined the statistical characteristics of four decision variables related to lane changes, with a specific emphasis on the gaps between vehicles. The study findings indicated that the gap between the subject vehicle and the preceding vehicle in the original lane was the only significant difference among mandatory and discretionary LC. Li et al. (2021) examined the dynamic impact of speed and distance factors on the LC process using a random parameter logit model, which accounts for heterogeneity in means and variances. Their findings highlighted the dynamic influences of vehicle clearance distance and speed on lane change decision-making. Zhou et al. (2020) delved into the determinants affecting discretionary lane changing behavior on urban roads, leveraging vehicle trajectory data collected from Southwest Road in Dalian, China. Employing both standard logit and mixed logit models, they scrutinized the data to understand the underlying dynamics. Their findings revealed that the mixed logit model had a superior performance in terms of model fit. Their findings underscored the pivotal role of driver heterogeneity in lane changing decisions, particularly concerning speed differences between the subject vehicle and leading vehicles, as well as the gap distance within the target lane.

After a careful review of prior studies (Park et al., 2015; Lee et al., 2016; Toledo et al., 2009; Alshehri and Abdul Aziz, 2022; Li et al., 2021; Zhou et al., 2020; Vechione et al., 2018), it can be concluded that our research significantly contributes to the existing body of literature regarding discretionary lane-changing behavior by addressing several critical gaps in existing literature. Our contributions are as follows: 1) unlike previous studies that predominantly focused on microscopic and macroscopic traffic characteristics (speed and density) (Knoop et al., 2012; Mullakkal-Babu et al., 2020; Toth et al., 2015; Tang et al., 2009; Bagheri et al., 2023; Farah et al., 2009; Zhang, 2004), we attempted to consider a wide array of explanatory variables including: road characteristics, socioeconomic factors, attitudinal traits, and specific traffic attributes; 2) while most of literature treated drivers as homogenous entities, our investigation acknowledges the inherent diversity among them. Leveraging the mixed logit model, we capture individual taste variations in LC behavior. This approach yields more accurate insights into the complex decision-making processes; 3) recognizing the influence of attitudinal aspects, we delve into driver aggressiveness. Unlike prior studies that merely relied on acceleration/deceleration metrics, we employ confirmatory factor analysis to identify aggressive drivers; 4) our research involves examining lane change behavior when drivers encounter queues downstream which receive less attention in prior studies; 5) most of prior research conducted in developed countries and less attention has been paid to this matter in developing countries which driving behavior is completely different from developed countries due to cultural norms, infrastructure, and policy approaches. In this regard, the objective of this paper is to develop an LC model to quantitatively analyze a wide range of explanatory factors affecting drivers' lane-changing decisions, specifically focusing on discretionary lane changes of cars in an urban road environment of Tehran, Iran, as one of the developing and most congested countries. Models in this paper were based on vehicle trajectory data collected from urban streets. To account for a complex traffic environment, probabilistic decision models were developed based on the random utility theory. A mixed logit model was fitted and compared with the standard logit model to accommodate heterogeneity among drivers.

This paper is structured as follows: Section 2 introduces the methodological approach including the research methodology and data description. Section 3 provides the main findings, while a critical discussion of findings is provided in section 4. Finally, the conclusions along with some concepts dealing with the future research developments, are outlined in Section 5.

2. METHODOLOGY

Considering the dichotomous nature of the dependent variable (do a lane change and stay on the current lane), in the research method section, the discrete choice model, particularly the binary logit and mixed logit models are discussed to introduce how the likelihood of discretionary lane changing is affecting by independent variables and which factors show the existence of taste variation in respondents' LC behavior. Niayesh highway, as a crowded urban highway, and its environment characteristics are introduced in Section 2.2. Beyond the utilization of video recording for data gathering, we also developed a survey for the drivers, requesting them to complete it at their earliest convenience. The questionnaire's sections and the corresponding explanation will be presented in this section, too. Finally, a descriptive analysis of the sample as well as the examination of lane change behavior based on the independent variables will be illustrated in Section 2.3.

2.1 Research method

Discrete choice models have become more prominent over recent decades when the dependent variable is discrete. Their structure is a probability-based model in which a user/alternative attempts to maximize the utility of choice through mathematical equations (Ben-Akiva & Lerman, 1985). Many analysts have made a great endeavor to develop different discrete choice models to relax the assumption of independence from irrelevant alternatives (IIA) in the fundamental multinomial logit (MNL) (Hensher et al., 2005). Among these models, the mixed logit model (MLM) is probably the most flexible one. It generalizes a standard MNL by allowing its parameter associated with the observed variable to vary with a known population distribution across individuals.

MLM is a widely used discrete outcome model that implies making three crucial decisions affecting the model specifications' quality. Such choices are as follows: 1) what variables to be included in the analysis, 2) which variables are to be modeled with random parameters, and 3) what density function do these parameters follow (Paz et al., 2019). The structure of this model is a generalized and logical structure of the well-known MNL, which can estimate any model with random utility, and addresses the three important deficiencies of the MNL by considering the difference in taste variation, the unlimited substitution pattern and correlation of unobserved factors (Train, 2009). It should be noted that MLM, unlike standard logit models and probit, is not limited to a specific distribution and is capable of finding unobserved preference heterogeneity (taste variation) in the behavior of individuals (Rezaei et al., 2011). In the context of discrete-choice modeling, the utility that a decision-maker n obtains from alternative i from the available choice set is defined as Equation (1):

1) $U_{ni} = V_{ni} + \varepsilon_{ni}$

where Vni is defined as the deterministic (representative) utility of alternative i for decision-maker n and εni is the unobserved and probabilistic utility term of option i for decision-maker n. In the MLM the unobserved part of the utility function consists of two contributions. The first is an arbitrary distribution and the second one, such as the standard logit model, consists of the extreme value distribution with the independent and identical distribution. Hence, it imposes fewer assumptions on the data, but it does not have a closed form as a probit model. The general form of the MLM is expressed as Equation (2):

2) $P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta$

where Pni is the probability that decision maker n chooses alternative i, f(β) is the density function and L_ni (β) is the probability that decision maker n chooses alternative i in MNL model which is a function of β parameter and defines as Equation (3):

3) $L_{ni}(\beta) = \frac{exp(V_{ni}(\beta))}{\sum_{j=1}^{J} exp(V_{nj}(\beta))}$

where V_ni (β) is the observed term of utility function which depends on the parameter. So, the choice probability function of the standard logit model is defined as Equation (4):

4) $P_{ni} = \frac{exp(b' X_{ni})}{\sum_{j=1}^{J} exp(b' X_{nj})}$

where X_ni is the observed attribute related to decision maker n and alternative i, b^' is the vector of observed attribute coefficients, which represents the equal weight of each explanatory variable between people. Distributions that are most commonly used for the density function of the β parameter include Normal, Lognormal, uniform, Triangular, and Johnson's SB distributions(Abbasi et al., 2022).

The probability of the MLM can result from the behavior of the maximization of utility in various officially equivalent methods, but it produces different interpretations. Random parameter models are the simplest and most widely used in previous studies (Ben-Akiva & Lerman, 1985). In these models, the defined utility function for alternative i, for choosing among j alternatives, is Equation (5):

5) $U_{ni} = \beta_n' X_{ni} + \varepsilon_{ni}$

where β_n^' is the vector of observed attribute parameters for decision-maker n which represents people's tastes. ε_(ni) is the random part of utility function which is an extreme value distribution which is identically and independently distributed. In this model, in contrast to standard logit model, β parameter with f(β) density function for decision-makers is different. f(β) is a function of θ parameters which describes the mean and homoscedasticity of β parameters in society. Random parameter model is defined as an integration of logit model over density function of β parameter, stated in Equation (6).

6) $P_{ni} = \int \frac{exp(\beta_n' X_{ni})}{\sum_{j=1}^{J} exp(\beta_n' X_{nj})} f(\beta|\theta) d\beta$

2.2 Study area and data collection

The selection of survey sites is the first and most important step in data collection. As part of the screening process, study sites were evaluated for the availability of commanding positions nearby (such as footbridges or tall buildings with good views for video recording), minimum lateral interference to traffic flow, and differentiation of mandatory and discretionary lane changes through video recording. An investigation of discretionary LC behavior along the Niayesh Highway in Tehran, Iran, was conducted using video recordings. The footbridge was equipped with two video cameras to record traffic flow on both sides. The study period was characterized by considerable and congested traffic flow downstream of the study direction, which made it easier to observe a sufficient number of lane changes. Afterward, the video recording was used to determine the explanatory variables such as the length of the vehicle, the number of lanes, the velocity, and that sort of thing, which will be further discussed in the next section, figure 1 illustrates the study area, which consists of four mainline lanes, lane 1 (leftmost) through lane 4 (rightmost). A 150-meter-long study area was used for the study. West-to-east was the direction in which data was collected (the study direction). Additionally, vehicle trajectories were extracted from the videos. The schematic of the variables related to the movement characteristics and the position of the vehicle is also illustrated in Figure 2. The separation of Figure 2 into Zone A and B is related to the existence of a merge area after Zone A finished.

As mentioned before, in addition to the video recording, a behavioral questionnaire has also been designed to determine the socioeconomic characteristics as well as driving behavior-related, road-related, and vehicle-related characteristics contributing to the lane-changing likelihood. Since there is a queue at the downstream of the study area (as

Fig 1. Video recording (drivers' behavior when encountering traffic jam)

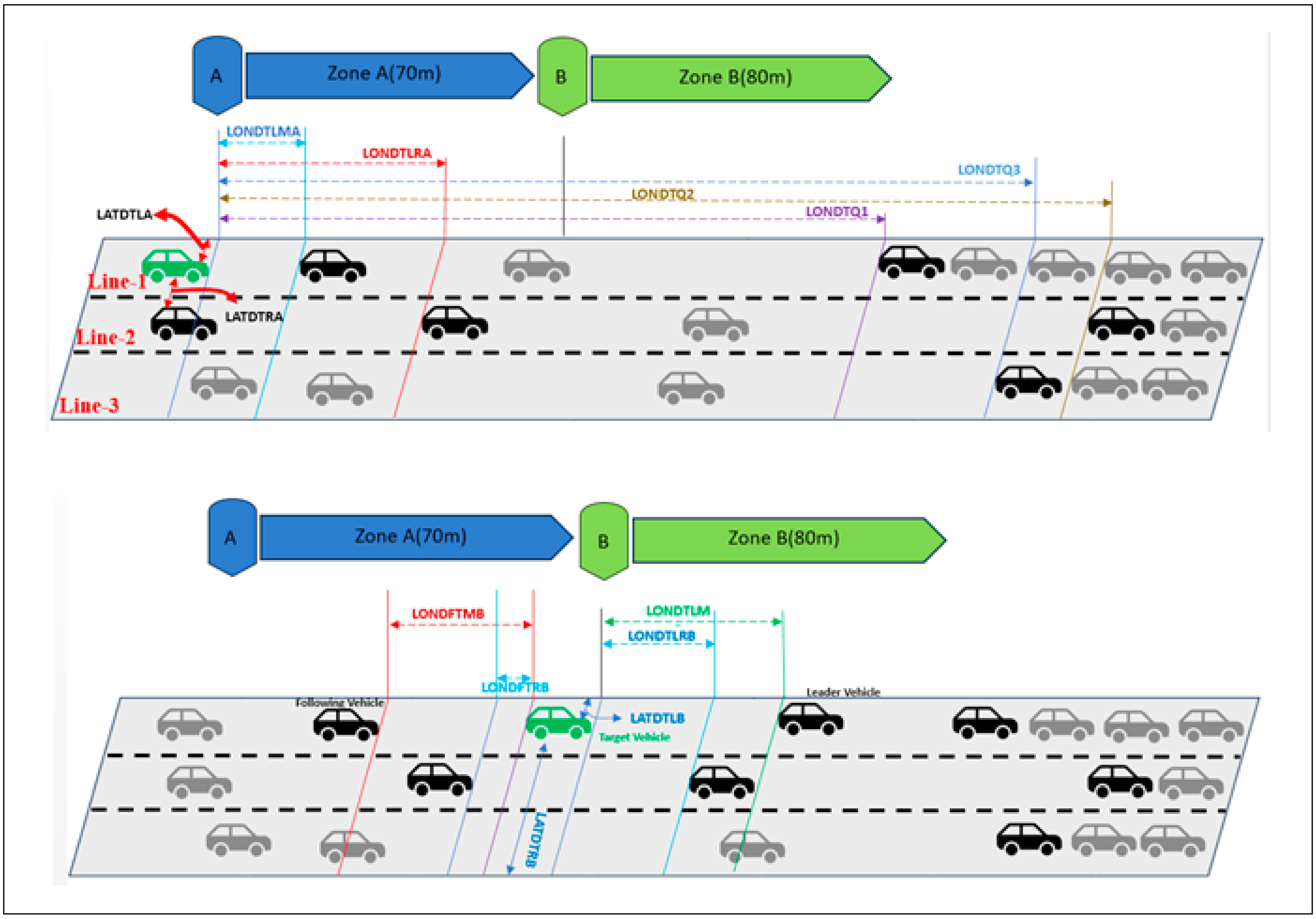

Fig. 2 Schematic of the variables related to the movement characteristics and the position of the vehicle

shown in Fig. 2), after the vehicles stopped in the queue, the survey was distributed among the drivers of target vehicles. They were solicited to fill out the survey at a suitable juncture and transmit it to the predetermined database. The questionnaire was bifurcated into two segments, with the objective of the survey articulated at the commencement. The initial segment encompassed socioeconomic factors such as age, gender, educational attainment, income, and experiences related to driving, accidents, and fines. The subsequent segment comprised an extensive array of inquiries pertaining to the respondents' driving behavior, thereby providing insights into their driving style, such as aggressiveness and law-evading.

2.3 Featuring the selected sample

Upon scrutiny of the received surveys, a total of 124 valid responses were earmarked for data analysis. A descriptive analysis of the socioeconomic characteristics of the research sample (Table 1) reveals that males constitute 74.8 % of the sample, with the remaining 25.2 % being females. In terms of age distribution, 60 % of the respondents are between 31-50 years old. With respect to educational attainment, approximately 40 % of the respondents hold a master's degree. The majority of the respondents (75 %) have more than 5 years of driving experience. Among them, 85 % experienced an accident in the last year. In terms of fine experience, 54.5 % of the respondents did not experience any fine in the last year. Households comprising four members account for 42.3 % of the sample. In case of income level, 37 % of the respondents belonged to an average-income level.

Variable	Category	Absolute frequency	Relative frequency (percentage)
Gender	Male: 1	92	25.2
	Female: 0	32	74.8
Age	21-30	16	13.0
	31-40	45	36.6
	41-50	29	23.6
	51-60	26	21.1
	61+	8	5.6
Education	High school diploma and associate:1	18	14.7
	Bachelor: 2	45	36.6
	Master: 3	50	40.7
	Doctorate: 4	11	8.0
Income	Low	25	20.3
	Average	45	36.6
	High	31	25.2
	Very high	23	17.9
Driving experience	Lower than 5	31	25.2
	More than 5	92	74.8
Fine experience in last year	Never	67	54.5
	1	21	17.1
	2	14	11.4
	3	10	8.1
	4+	12	8.9
Accident experience in last year	0	0	0
	1	107	86.3
	2+	16	13.7

Table 1. Results of travel time distribution analysis

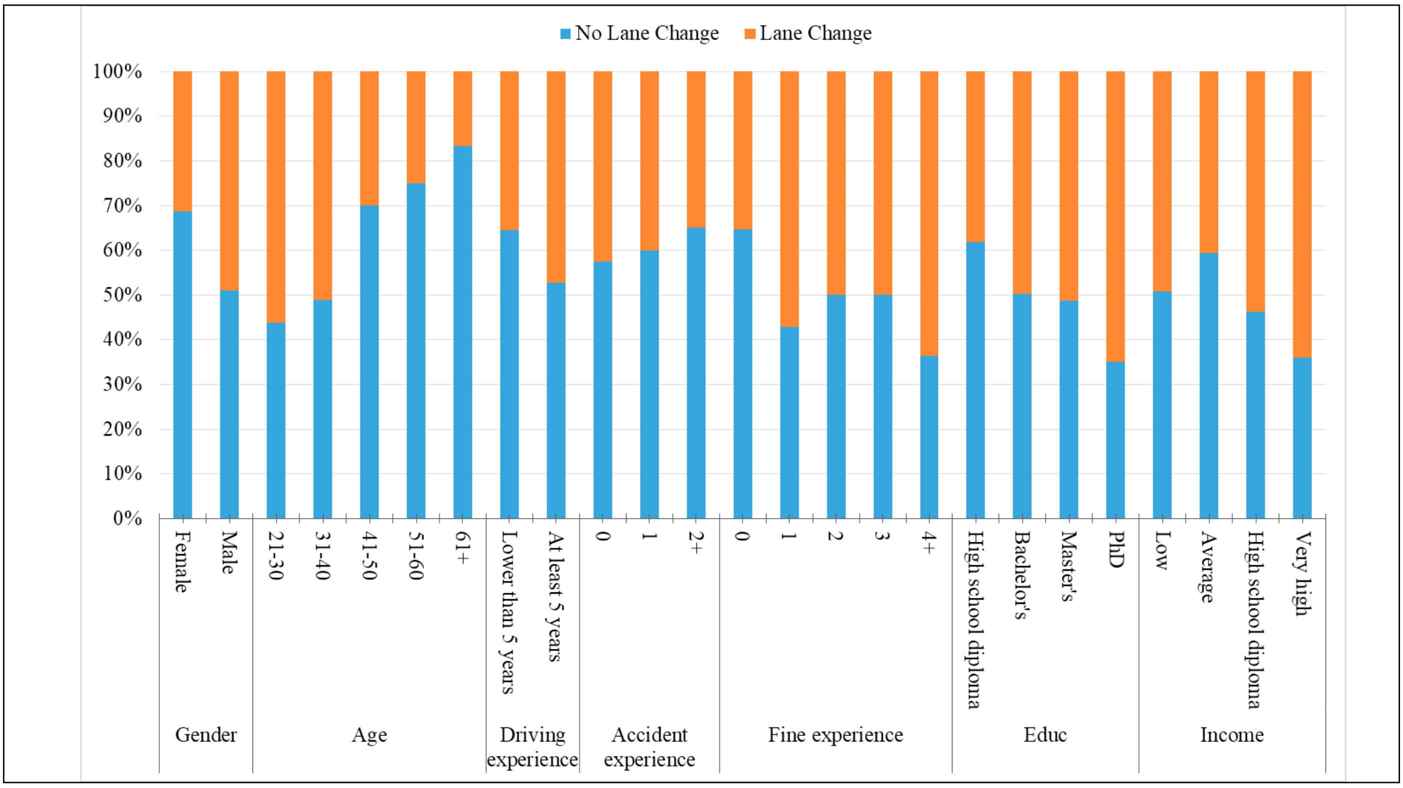

Fig. 3. Lane changing willingness stratified by socioeconomic and driving-related characteristics

rience any fine in the last year. Households comprising four members account for 42.3 % of the sample. In case of income level, 37 % of the respondents belonged to an average-income level.

The lane changing behavior of the respondents has been stratified by several socioeconomic and driving-related features (Figure 3). As it can be seen, in case of gender, men are more willing to lane changing in comparison with women considering their higher level of risk-taking. When it comes to age, it can be found that with the increase in the age, the drivers' willingness to change their lanes is also decreased. It can be due to the fact that older drivers have a lower reaction time and risk-taking nature. As driving experience increases, the drivers' willingness to discretionary lane changing will also increase showing that they might be more confident in their driving skills. However, when drivers experience more accidents, they are less likely to do a lane changing. On the other hand, a reverse trend can be seen when it comes to fine experience, showing the ineffectiveness of the fines in reducing dangerous driving behaviors. Finally, when it comes to education and income levels, it can be observed that an increase in both leads to an increase in the willingness to change lanes.

3. ESTIMATION RESULTS

To identify the impact of driving behavior, attitudinal factors, and socioeconomic characteristics on the likelihood of lane changing in the face of downstream queue, first, a binary logit model has been estimated in the Nlogit software (Table 2). The reason for using such model is to fit two utility functions with the alternatives of the probability of lane change (LC) and the probability of no lane change (NLC). It is worth mentioning that due to the trial-and-error nature of modeling, a large number (about 300) of binary logit models have been estimated with a stepwise approach. In this approach, all variables are considered in the utility function one by one and if they have a significant effect and logical sign, they will be preserved in the utility function, otherwise, they will be removed from the model (Abbasi et al., 2023; Abbasi et al., 2022). Considering the estimated coefficients and the value of the goodness of fit coefficient, it can be concluded that all the variables present in the model have a logical sign and the value of the likelihood ratio index (47.7 %), as an indication of goodness of fit, indicates a desirable fit of the model on the research data. Further, we have calculated the percent correct criteria in order to assess the prediction as well as accuracy of the estimated model. The percent-correct criteria for the estimated model is 85.5, indicating a high accuracy of the proposed model.

The variable of the target vehicle's speed (VT) has been found to be significant (β: 0.144, p-value= 0.003) and positively associated with a higher likelihood of lane changing. This indicates that as the speed of the target vehicle increases, the probability of changing lanes when encountering a queue will also increase. This is due to the nature of discretionary lane changing which drivers move to the adjacent lane in order to reach his/her desired speed. This finding is also well-established in previous studies (Park et al., 2015; Schmidt et al., 2021). The lateral distance between the target vehicle and the vehicle or obstacle on the left side (LATDTLB) has been found to be significant in the lane change utility function, with a positive sign and a significance level of 1 % (β: 0.499, P-value= 0.001). This indicates that as the lateral distance between the target vehicle and the vehicle or obstacle on the left increases, the probability of changing lanes when encountering a queue will also increase which is in accordance with prior studies' findings (Dilipan et al., 2022; Park et al., 2015). The variable of law evasion as an attitudinal variable has been found to be significant in the lane change utility function, with a positive coefficient and a significance level of 1 % (β: 2.384, p-value: 0.006). This indicates that as the level of law evasion increases, the probability of changing lanes when encountering a queue will also increase. It suggests that drivers who tend to evade laws are more likely to change lanes to avoid slower-moving vehicles. The individuals who frequently pass through intersections lacking traffic violation cameras during yellow lights (YELOW5) have been found to significantly affect the lane-changing behavior with a positive coefficient sign and a significance level of 10 % (β: 3.353, p-value: 0.065). This suggests that individuals who usually pass through yellow lights at intersections without cameras are more likely to change lanes when faced with traffic. The estimated coefficient of AGE41-50 variable (β: −1.568, p-value: 0.035) indicates that individuals in the age group of 41-50 years are less willing to conduct a discretionary lane changing behavior when facing a downstream queue in comparison with other drivers within other age groups. Among the reasons for this, as suggested by previous studies, these individuals, due to their age, have lower risk-taking and reaction time features, which will decrease the likelihood of lane changing among them (Lavallière et al., 2010; Ye et al., 2022). The variable of drivers who do not drive extremely close to the preceding vehicle and do not frequently flash their headlights (NEARLIG1) has been significant with a negative coefficient and a significance level of 1% (β: -1.672, p-value= 0.008), indicating a lower likelihood of lane changing when facing with a downstream queue.

On the other hand, the factor contributing to the likelihood of not lane changing is as follows. The variable of drivers who merely conduct a lane change, when faced with pavement damage (PAVELCNO) has been significant with a positive coefficient sign and a significance level of 1 % (β: 1.640, p-value= 0.009). This indicates that these individuals, compared to others, are less likely to change lanes when faced with a downstream queue. The preceding vehicle speed variable (VL3540) has a significant positive coefficient at the 5% significance level (β: 1.441, p-value = 0.046) in the not lane-changing function. This indicates that if the speed of a preceding vehicle is within the range of 35 to 40 km/h, the probability of not changing lanes will increase. This finding is also well-aligned with previous studies (Park et al., 2015; Schmidt et al., 2021). The estimated coefficient of R-OVERT indicating the drivers who rarely move to the right side of the road when faced with traffic jams, has been found to be significantly associated with the probability of not changing lanes when faced with a queue. The coefficient of RGAV2 is positive (β RGAV2= 2.608) and statistically significant (p-value= 0.007) in the utility function of non-lane-changing behavior. This suggests that such individuals are more likely to maintain their lane when confronted with a queue. The significant coefficient of the lateral distance between the target vehicle and the right-side obstacle in zone B (LATDTRB) is negative (β: -0.220, p-value = 0.020), indicating that as the lateral distance between the target vehicle and the right-side obstacle in zone B increases, the probability of not changing lanes when faced with a queue decreases. The findings of Dilipan et al. (2022) and Park et al. (2015) also confirm this matter. The coefficient of ACCEXP2 variable indicates that being a driver who has experienced at least two accidents in the past year is negatively associated with the likelihood of no lane-changing behavior (β: -4.656, p-value: 0.024) and this is a significant coefficient at a 5% level. This indicates that individuals who have experienced two accidents in the past year are more likely to change lanes when faced with a queue.

4. DISCUSSION

The marginal effects have been used to identify the most influential factors in lane changing behavior. Marginal effects are defined as changes in probability of choosing the dependent variable relative to an independent variable that changes by only one unit, while all other variables remain the same. For example, by increasing the target vehicle's speed by 1 kilometer per hour, the probability of changing lanes rises by 1.8%. Regarding dummy variables, such as Age 4150, it is important to note that belonging to this age group, compared to the other age groups, will result in a decrease of approximately 20% in the likelihood of changing lanes. As a consequence of the values of the marginal effects, it can be concluded that law-evading behavior and crossing the yellow light at intersections without violation recording cameras are the most influential factors that increase the likelihood of lane changes. On the other hand, the most influential factor associated with not changing lanes is related to individuals who rarely move to the right side of the road (right shoulder) when facing downstream congestion.

Regarding the lack of closed-form in the MLM model, the simulation-based maximum likelihood method used to estimate parameters vector and 500 Halton draws were utilized (Table 3). Some related distributions were considered to identify the proper distribution of the random parameters. Finally, normal distribution was statistically significant with coefficients at 90 % or higher confidence level.

The only coefficient indicating the existence of taste variation among the drivers in lane changing behavior was LatDTLB. It is a random parameter and normally distributed with the mean of 0.708 and the standard deviation of 0.403 in the lane change function. It indicates that there is an unobserved heterogeneity and taste variation among drivers with regard to the lateral distance of the target vehicle from a left obstacle or car at Zone B when are willing to conduct a lane changing maneuver.

5. CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

For many years, discretionary lane-changing, as a crucial aspect of traffic flow, has been extensively studied. The majority of current research on discretionary lane-changing assumes that drivers exhibit a homogenous behavior. Nevertheless, in real-world traffic flows, heterogeneity between drivers is evident, but most of it is unobserved. Moreover, a few studies considered the socioeconomic as well as driving style characteristics in addition to the traffic environment characteristics. Using data on discretionary lane changing in Tehran, Iran, a congested capital of a developing country, the paper estimates a mixed logit model. Estimation results show that there is unobserved heterogeneity and taste variation among drivers with regard to the lateral distance of the target vehicle from the left obstacle or car when they are willing to conduct a lane changing maneuver. Among the non-random parameters, speed of a target vehicle, being a law-evading driver, disregarding yellow traffic signals at intersections, lateral distance of a target vehicle from right/left cars, and experiencing at least two accidents are positively associated with a higher likelihood of lane changing when a driver encounters a downstream queue. However, the likelihood of lane changing is negatively correlated with older drivers, drivers who do not drive too close to the preceding vehicle, drivers who merely alter lanes when faced with pavement damage, speed of the preceding vehicle being in the 35 to 40 km/hr range, and drivers who seldom use the right side of the road when facing traffic jams.

Finally, some insightful findings have been achieved regarding the determinants behind the likelihood of lane changing which can help to future research. A number of fruitful directions can be pursued in future work. It is recommended to examine the effect of information on road, lighting, and weather conditions on the likelihood of lane

Variable	Definition	Coefficient	t-stat	Marginal effect
Doing a discretionary lane change utility function				
Constant	Alternative-specific constant	– 10.132***	– 3.47	-
VT	Speed of target vehicle	0.144***	2.97	0.0182
LatDTLB	Lateral Distance of Target Vehicle from Left obstacle or car at Zone B	0.499***	3.23	0.0630
Age41-50	If driver's age is between 41 and 50 years old=1, otherwise=0	– 1.568**	– 2.11	– 0.1982
Lawevading	Being a law-evading driver	2.384***	2.75	0.3014
Nearlig1	Drivers who consistently maintain a safe distance from the preceding vehicle and refrain from frequently flashing their headlights	– 1.672***	– 2.65	– 0.2114
Yellow5	Drivers who frequently disregard the yellow traffic signal at intersections equipped with traffic violation detection cameras.	3.353*	1.84	0.4239
Not Doing a discretionary lane change utility function				
PAVENLC	Drivers who merely change lanes when faced with pavement damage.	1.639***	2.61	0.1762
LatDTRB	Lateral Distance of Target Vehicle from right obstacle or car at Zone B	– 0.220***	– 2.33	– 0.0237
VL35-40	If the speed of preceding vehicle between 35 and 40 km/h= 1; otherwise= 0	1.441**	2.00	0.1548
ACC-EXP2	If a driver experienced at least 2 accidents in last year= 1; otherwise= 0	– 4.656**	– 2.25	– 0.5003
R-OVERT	If a drivers rarely move to the right side of the road when faced with traffic jams= 1; otherwise=0	2.607***	2.69	0.2802
	Number of observations	248		
	LL(β)	– 44.966		
	LL(C)	– 85.158		
	LL(0)	– 85.950		
	ρ_c^2	0.472		
	ρ_0^2	0.477		

Table 2. Estimation result of binary logit model regarding the lane changing decision

Variable	Definition	Coefficient (S.D.[1])
Doing a discretionary lane change utility function		
Constant	Alternative-specific constant	– 13.357***
VT	Speed of target vehicle	0.195**
LatDTLB	Lateral Distance of Target Vehicle from Left obstacle or car at Zone B (**Random parameter**)	0.708** (0.403*)
Age41-50	If driver's age is between 41-50 years old=1, otherwise=0	– 2.262*
Lawevading	Being a law-evading driver	3.032**
Nearlig1	Drivers who consistently maintain a safe distance from the preceding vehicle and refrain from frequently flashing their headlights	– 2.255**
Yellow5	Drivers who frequently disregard the yellow traffic signal at intersections equipped with traffic violation detection cameras.	4.605*
Not Doing a discretionary lane change utility function		
PAVENLC	Drivers who merely change lanes when faced with pavement damage.	2.308**
LatDTRB	Lateral Distance of Target Vehicle from right obstacle or car at Zone B	– 0.276**
VL35-40	If the speed of preceding vehicle between 35-40 km/h= 1; otherwise= 0	1.544*
ACC-EXP2	If a driver experienced at least 2 accidents in last year= 1; otherwise= 0	– 6.419**
R-OVERT	If a drivers rarely move to the right side of the road when faced with traffic jams= 1; otherwise=0	3.515**
	Number of observations	248
	LL(β)	- 43.98
	LL(C)	- 85.95
	LL(0)	- 85.95
	$\boldsymbol{\rho_c^2}$	0.4835
	$\boldsymbol{\rho_0^2}$	0.4883

1 S.D. accounts for the standard deviation of random parameters

Table 3. Estimation result of mixed logit model regarding the lane changing decision

changing. By expanding this data, it will be possible to incorporate heterogeneity across vehicles directly into statistical models. Furthermore, future research could address the issue of transferability. To determine whether model estimation results can be transferred spatially to different locations, model estimation results from the same location at different times can be compared, and data from the same location in different time periods may be compared to determine if the lane-changing behavior is stable over time, or if drivers are altering their behavior in response to changes in vehicle technology and other factors.

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