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Discretionary lane-changing behavior at downstream queues, case of choice modeling

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Abstract

Discretionary Lane-Changing (DLC) behavior significantly impacts various facets of traffic flow, including capacity, shock waves, and safety. Understanding the determinants behind DLC behavior is crucial. In this study, we investigate the factors influencing DLC in congested traffic using a combination of video recording and survey methods. We employ a binary logit model to examine the impact of a wide range of explanatory variables such as speed, lateral distance, aggressiveness, age, and driving styles on DLC behavior. Our estimation results reveal that socioeconomic, driving style, and road environment variables all play a significant role in lane-changing. Specifically, several parameters exhibit positive associations with the likelihood of lane-changing when drivers encounter downstream queues. These parameters include the speed of the target vehicle, law-evading behavior, disregard for yellow traffic signals at intersections, lateral distance from adjacent cars, and facing at least two accidents. Our empirical findings shed light on the factors affecting DLC and can enhance the performance of traffic flow models.

Keywords – lane-changing behavior, video recording, binary logit model, discretionary, traffic flow

1. Introduction

While driving vehicles on regular roads constitutes a common mode of daily transportation, navigating roads with heavy traffic introduces a range of unforeseen circumstances, including emergency lane changes and abrupt braking [1]. These conditions can lead to a cascade of traffic accidents. Lane-changing behavior, a fundamental driving action, significantly influences traffic flow during commuting, driving planning, and overall driving safety [2, 3]. It constitutes a prevalent traffic behavior inherent to the driving process and serves as an essential component of overall driving behavior. Specifically, lane-changing refers to the maneuver where a target vehicle transitions from its current lane to another adjacent lane. This maneuver serves dual purposes: enhancing driving conditions or facilitating exit from the roadway [4]. The process of lane-changing involves multiple vehicles across adjacent lanes, and it transpires while vehicles are in motion, interacting with their surrounding counterparts [5]. In general, when a vehicle executes a lane change, it can result in a reduction of overall traffic capacity and the generation of shock waves that propagate through both lanes [6]. Notably, frequent lane change operations, especially in areas of confluence, divergence, and weaving, can create bottlenecks on freeways. These bottlenecks, in turn, contribute to traffic collapse during heavy traffic conditions [7]. A Lane change-related traffic accidents constitute 5% of the overall accident count, with a significant proportion (75%) attributed to hazardous lane-changing maneuvers by drivers [8]. According to data from the National Highway Traffic Safety Administration (NHTSA), lane changes account for a substantial portion of annual traffic accidents. Specifically, an estimated 240,000 to 610,000 accidents are attributed to drivers changing lanes annually, resulting in a minimum of 60,000 injuries stemming from such lane-changing maneuvers [9]. In the year 2019, a count of 10,706 traffic accidents resulted from overtaking maneuvers and lane changes, constituting approximately 4.32% of the overall traffic accidents in China [10]. Notably, empirical evidence underscores the critical role of accurate lane change decisions, as approximately 75% of traffic accidents stem from driver errors during this maneuver. These statistics underscore the significance of lane change behavior in the context of road safety and warrant careful attention from both researchers and policymakers.

Lane change behavior categorized into two distinct types of lane changes: mandatory lane change and discretionary lane change [11]. These behaviors are critical for achieving driving objectives while maintaining adherence to traffic regulation. Mandatory lane change refers to the behavior that a vehicle must execute to fulfill its intended driving purpose. When a vehicle approaches an intersection, it encounters lane guide markers ahead. These markers signal the need to prepare for a lane change to the left. Vehicles nearing the end of their current lane also anticipate a leftward lane change. Buses often exhibit this behavior when transitioning from the inside lane to the outside lane near a bus stop [12]. However, discretionary lane change occurs when a vehicle adjusts its position to pursue higher speeds or find more open driving space. The intent to change lanes arises when the vehicle's following speed falls below 0.75–0.85 times the desired speed [13]. The vehicle evaluates two key elements before changing to an adjacent lane: Is the current vehicle eligible to use the adjacent lane based on traffic rules? And is there sufficient space in the adjacent lane to accommodate the lane change?

Comprehending the diverse behaviors exhibited by drivers during the driving process is a multifaceted endeavor. To achieve this understanding, an exploration of the driving behaviors across various drivers becomes essential. This investigation delves into the cognitive processes, decision-making mechanisms, and behavioral patterns of distinct drivers under diverse conditions. Researchers approach the modeling of lane change behavior by meticulously collecting traffic data and accounting for variables of uncertainty encountered on the road. Lane change behavior is influenced by a multitude of factors, including driver characteristics (such as gender, driving experience, and age), distinct traffic environments (such as urban roads, expressways, and township roads), vehicle dynamic performance, and temporal variations related to morning, afternoon, and evening travel. Ma et al. [14] conducted a rigorous mathematical analysis to investigate the frequency of lane changes by drivers. Their study revealed a robust correlation between frequent lane changes and specific contextual factors, including traffic environment, vehicle size (particularly small cars), and traffic flow density. Notably, aggressive driving behavior, characterized by frequent lane changes, predominantly emanated from individual drivers. Further insights into lane-changing behavior were gleaned by Vechione et al. [15], who meticulously compared driver actions during both mandatory and discretionary lane changes. Their focus centered on four decision variables, with particular attention to the gaps between vehicles. Intriguingly, the study findings highlighted that the gap between the subject vehicle and the preceding vehicle in the original lane emerged as the sole significant distinction between mandatory and discretionary lane changes.

1.1. Research objectives

To execute a judicious lane change, drivers must engage in precise lane change assessment and decision-making. Enhancing the accuracy of lane change prediction models hinges on incorporating relevant contextual factors, including the driver's cognitive state and pertinent information about the vehicle and surrounding traffic. This approach underscores the importance of considering both internal (driver-related) and external (environmental) cues when designing effective lane change prediction systems for enhanced driving safety and efficiency. Therefore, our objective is to develop a quantitative lane change (LC) model that explores a wide range of factors influencing drivers' discretionary lane-changing decisions. We focus on cars in the urban road environment of Tehran, Iran—an exemplar of a congested developing country. Our models are informed by vehicle trajectory data collected from urban streets, providing valuable insights into this critical aspect of traffic dynamics.

This paper is organized as follows: In Section 2, a review of prior studies has been conducted to understand the research gaps. In Section 3, we present the methodological approach, encompassing the research methodology and data description. Section 4 offers a critical analysis of the primary findings. Lastly, Section 5 outlines the conclusions and introduces concepts related to future research developments.

2. Theoretical background

Logit models serve as prevalent empirical frameworks for analyzing lane change behavior, particularly in the context of constructing probabilistic models for vehicle lane-changing decision-making (Table 1). These models primarily leverage the driver's observational data and estimated parameters to characterize the decision-making process involved in lane changes. Anastasopoulos et al. [16] enhanced the performance of the logit model by incorporating influential factors such as vehicle spacing, speed difference, and traffic flow density. They employed detailed data related to road shape, road condition, weather conditions, and traffic characteristics. The utilization of such detailed data significantly improved the model's accuracy. Farhi et al. [17] proposed a logit-based lane allocation model to analyze multi-lane traffic flow from a macroscopic viewpoint. Within this framework, each available lane is associated with a distinct utility value for the driver during driving. Consequently, the driver chose the lane that maximizes his/her utility. The model is mathematically formulated using a system of conservation laws, with flux functions that are implicitly defined and exhibit smooth behavior. Lane-changing around large commercial vehicles presents a formidable challenge, with potentially severe consequences arising from hazardous maneuvers. In an effort to comprehensively examine the interplay between collision factors and the severity of commercial vehicle lane change incidents, Adanu, E.K. et al. [18] developed a mixed logit model—incorporating both fixed and random parameters—using Alabama traffic crash data spanning the period from 2009 to 2016. Approximately 4% of these accidents result in severe outcomes, while more than 50% are attributed to driver error. A comprehensive model evaluation revealed several critical factors influencing the severity of crashes during lane changes including environmental conditions such as dark and unlit sections significantly increase the likelihood of severe lane change accidents. In terms of driver demographics, involvement of older drivers, those who exhibit negligence, or female drivers correlates with increased crash severity. Moreover, motorways with more lanes experience fewer severe lane change accidents. Lane-changing demands a considerable degree of driving expertise from the driver, particularly posing challenges for young, novice drivers and older individuals. Li et al. [19] employed a random parameter logit method to analyze the mean and variance heterogeneity associated with distance- and speed-related factors using a micro-vehicle trajectory dataset. Their study shed light on the nuanced influences of vehicle clearance distance and speed on LC decision-making.

Zhou et al. [20] delved into the determinants shaping discretionary lane-changing behavior on urban roads. Leveraging vehicle trajectory data collected from Southwest Road in Dalian, China, they meticulously analyzed the data using both standard logit and mixed logit models. Their findings underscored the pivotal role of driver heterogeneity in LC decisions, particularly with regard to speed differences between the subject vehicle and leading vehicles, as well as the gap distance within the target lane. Sun and Elefteriadou [21] conducted an empirical investigation utilizing the focus group method to explore various facets of discretionary lane changes. Specifically, their study delved into the typology of drivers, the likelihood of engaging in lane changes, and the underlying determinants influencing the execution of such discretionary maneuvers. In a complementary study, Sun and Elefteriadou [22] conducted an in-vehicle experiment, wherein they formulated probability functions tailored to individual lane change scenarios. Notably, their approach incorporated driver-specific characteristics that had been previously overlooked by existing models. Furthermore, Alshehri and Abdul Aziz [23] employed a logistic stepwise selection procedure to scrutinize the impact of vehicle attributes (such as length and width) and flow characteristics (including headways and lead-lag gaps) on the decision-making process associated with lane changes. Factors contributing to an augmented likelihood of discretionary lane changes encompassed 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). Park et al. [24] employed a logistic regression model to discern the impact of disparities in speed and density between adjacent lanes on lane change (LC) probabilities. Their findings underscored the significant influence of these factors on the likelihood of LC events. In a complementary vein, Lee et al. [25] adopted an exponential probability model to predict LC behavior. Their approach hinged upon assessing differences in lane speeds and lead gaps. By quantifying these variables, they could estimate the probability of a vehicle executing a lane change maneuver. Furthermore, Toledo et al. [26] contributed to this field by constructing a probabilistic lane change model grounded in utility theory. Unlike previous models, theirs accounted for both mandatory and discretionary lane changes concurrently. This holistic approach recognized that drivers make lane changes for various reasons, including adherence to traffic rules and personal preferences. Matcha et al. [27] also developed a model to analyze and predict how vehicles change lanes at merge sections in mixed traffic conditions. They explored factors such as traffic volume, vehicle speed, and drivers' behavior to understand the dynamics of lane-changing maneuvers. Zhang et al. [28] proposed a model for lane-change decision-making in driving that is based on learning algorithms and takes into account the individual driving style of the driver and contextual traffic information. Li et al. [29] studied the duration of discretionary lane changes, which are lane changes made by drivers based on their own judgment rather than external factors like lane closures or merging vehicles. The study takes into account the heterogeneity of drivers, meaning that different drivers may exhibit varying behaviors when making lane changes.

After a careful review of prior research, it can be concluded that our research significantly contributes to the existing literature on discretionary lane-changing behavior by addressing critical gaps. Unlike previous studies that primarily focused on microscopic and macroscopic traffic characteristics (such as speed and density), our study considers a comprehensive set of explanatory variables. These variables encompass road characteristics, socioeconomic factors, attitudinal traits, and specific traffic attributes.

Tab. 1 - A brief review of prior studies within the field of the likelihood of conducting a lane-changing behavior

Study	Method	Sample size	Explanatory Variable		
			Socioeconomic	Traffic & environment	Driving style
Li et al.	Mixed logit	3492		✓	✓
Li et al.	Mixed logit	543		✓	
Zhou et al.	Mixed logit	408		✓	
Sun and Elefteriadou	Focus group and in-vehicle experiments	15		✓	
Alshehri & Abdul Aziz	Logistic regression	-		✓	
Park et al.	Logistic regression	-		✓	
Lee et al.	Exponential probability	-		✓	
Toledo et al.	Logit	442		✓	

Additionally, our research sheds light on lane change behavior when drivers encounter downstream queues, an aspect that has received less attention in prior studies. Furthermore, while much of the existing research has been conducted in developed countries, our study bridges a gap by examining lane-changing behavior in a developing country context. The distinct driving behavior in developing countries, shaped by cultural norms, infrastructure limitations, and policy approaches, necessitates a tailored analysis.

3. Methodology

This section outlines the research methodology, including the discrete choice model (specifically the binary logit model) used to analyze the likelihood of discretionary lane-changing. We explore how independent variables contribute to this behavior. Additionally, we introduce the study area, Niayesh highway, a busy urban road, and discuss its environmental characteristics. Data collection methods, including video recording and a driver survey, are detailed. Finally, we present a descriptive analysis of the sample and examine lane change behavior based on independent variables.

3.1. Binary Logit model

In the context of discrete choice models, a fundamental premise is that individuals encounter a collection of alternatives. Their preference for each alternative can be quantified using a utility or attractiveness criterion. This utility is influenced by both the attributes of the alternative itself and the characteristics of the decision maker, as expressed by Equation 1.

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

where, the deterministic utility (Vni) of alternative (i) for decision-maker (n) is explicitly defined. Additionally, the unobserved and probabilistic term of utility function (i.e. eni) associated with alternative (i) for decision-maker (n) plays a crucial role. The error terms are assumed to follow a Gumbel distribution, characterized by independently and identically distributed (IID) properties.

The binary logit closed-form, as proposed by Train [27], quantifies the probability that decision maker (n) selects alternative (i) (Equation 2).

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{m \in C_n} e^{V_{nm}}} \tag{2}$$

In our study, we employed t-statistics to assess the significance of explanatory factors at specified confidence levels (90%, 95%, and 99%). Additionally, we conducted a likelihood ratio test, utilizing the chi-square distribution (as represented by Equation 3), to rigorously examine the statistical significance of the proposed models at various stages of the modeling process [28].

$$-2\left[LL(0) - LL(\beta)\right] > X^2_{N,1-\alpha} \tag{3}$$

where, N represents the number of estimated parameters resulting from the application of constraints within the model and the significance level denoted by α. Furthermore, we employed the likelihood ratio index, as expressed by Equations 4 and 5, to rigorously assess the goodness of fit of the proposed models.

$$\rho_0^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{4}$$

$$\rho_C^2 = 1 - \frac{LL(\beta)}{LL(C)} \tag{5}$$

where ρ_0^2 shows the improvement in the log-likelihood function value at convergence (LL(β)) relative to the log-likelihood function value at zero (LL(0)). Additionally, we assess the improvement in the log-likelihood function value at convergence (LL(β)) compared to the log-likelihood function value when considering only the constant term ((LL(c)) through ρ_c^2 [27].

The adequate sample size was determined using Equation 6 [13].

$$n_0 = \frac{pqz^2}{e^2} \tag{6}$$

where the sample size is n_0, the standard error at the considered significance level is z, the proportion of the population with the attribute in question is p, q is $1-p$, and the acceptable sample error is e.

3.2. Case study

In the context of transportation research, the initial and pivotal step in data collection involves strategically selecting survey sites. During this screening process, study locations are meticulously assessed based on several criteria. These criteria include proximity to commanding positions, such as footbridges or tall buildings, which offer optimal views for video recording. Additionally, the chosen sites should minimize lateral interference with traffic flow. Furthermore, the ability to differentiate between mandatory and discretionary lane changes through video observations is crucial.

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

In our specific investigation of discretionary lane change behavior along the Niayesh Highway in Tehran, Iran, we employed video recordings. Niayesh highway features a speed limit of 90 kmph, a route width of 13 meters, three main lanes for traffic flow, and an access ramp for merging onto or exiting the highway (Figure 1).

3.2.1. Data collection

A strategically positioned footbridge, equipped with two video cameras, facilitated the comprehensive capture of traffic flow from both sides. Notably, the study period coincided with significant and congested traffic downstream, providing ample opportunities to observe a sufficient number of lane changes. All observations were collected between 6:45 a.m. and 7:45 a.m. in the morning of 29th April, 2023, a typical weekday, without the drivers being informed. This rigorous approach to site selection ensures data quality and enhances our understanding of driver behavior within the complex dynamics of traffic flow.

Subsequently, the video recording was used for evaluating the traffic data and drivers' decision such as vehicle type, lateral distance to adjacent vehicle or obstacle, longitudinal distance of target vehicle to following and leader vehicle, speed of vehicles (km/h), and lane-changing decision of drivers. Using some semi-automated techniques such as tracking the trajectories of vehicles in the video, we extracted mentioned parameters and manual intervention has been conducted to correct any errors in trajectory tracking. These variables, which will be expounded upon in the subsequent section, play a pivotal role in our analysis. Figure 1 visually delineates the study area, comprising four mainline lanes—ranging from the leftmost (Lane 1) to the rightmost (Lane 4). The study area spanned a length of 150 meters. Data collection occurred in a west-to-east direction, aligning with the designated study direction. Furthermore, we meticulously extracted vehicle trajectories from the video footage. Figure 2&3 provide a schematic representation of the variables associated with movement characteristics and vehicle positioning. Notably, the division of Figure 2&3 into Zones A and B corresponds to the presence of a merge area following the completion of Zone A. As it can be seen, the length of study area (150 meters) divided into two section including Zone A (first 70m, before the location that the ramp joins the main lanes) and Zone B (the remaining 80m, after the middle curb is finished).

As previously mentioned, alongside the video recording component, a meticulously designed behavioral questionnaire was employed to ascertain a comprehensive understanding of the factors influencing lane-changing likelihood. This questionnaire encompassed a multifaceted exploration of socioeconomic characteristics, driving behavior-related attributes, road-related factors, and vehicle-specific features.

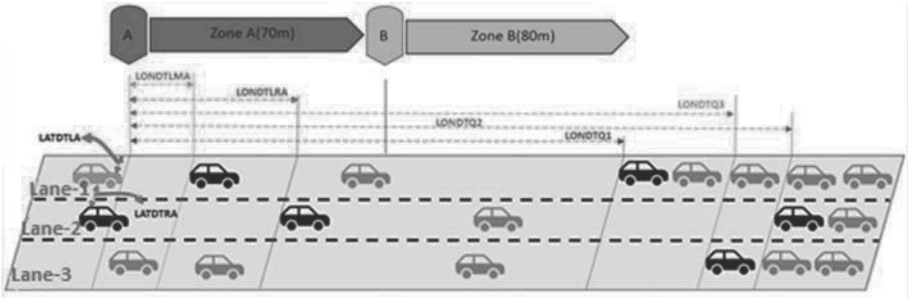

Fig. 2 - A schematic representation of variables
associated with movement characteristics and vehicle location (main lanes)

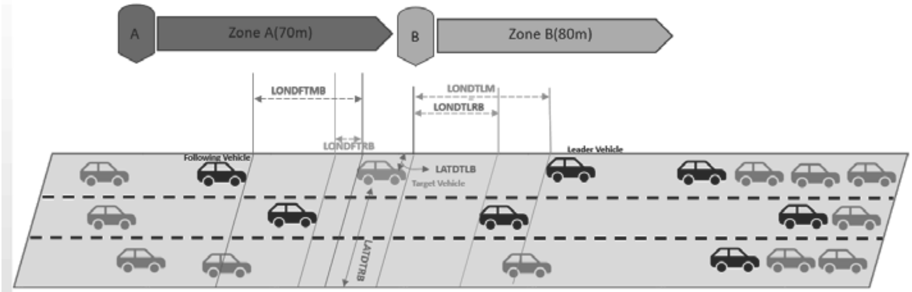

Fig. 3 - A schematic representation of variables
associated with movement characteristics and vehicle location (main lanes)

Given the context of the study area, where a queue of vehicles formed downstream (as depicted in Figure 2&3), the survey administration occurred opportunistically. Specifically, when vehicles came to a halt within the queue, drivers were approached and invited to participate in the survey. They were requested to complete the questionnaire at their convenience and subsequently transmit the responses to a pre-established database. Each questionnaire has a unique ID indicating which driver has completed the survey and we matched the ID with the corresponding measurements derived from the video data. The questionnaire was thoughtfully divided into two distinct segments. The initial segment focused on socioeconomic variables, including age, gender, educational attainment, income, and relevant experiences related to driving, accidents, and traffic fines. These factors provided essential context for understanding individual decision-making processes within the driving context. The subsequent segment delved into a comprehensive array of inquiries specifically targeting respondents' driving behavior. This section aimed to uncover insights into driving styles, encompassing aspects such as aggressiveness and tendencies toward law-evading behaviors.

3.3. Sample characteristics

Upon meticulous examination of the collected surveys, a total of 124 valid responses were earmarked for subsequent data analysis. A descriptive scrutiny of the socioeconomic characteristics within the research sample (as summarized in Table 2) reveals the following key findings. In terms of gender distribution, males constitute 74.8% of the sample, while the remaining 25.2% are females. When it comes to age groups, approximately 60% of the respondents fall within the age range of 31-50 years. In terms of educational attainment, approximately 40% of the respondents hold a master's degree. Households comprising four members account for 42.3% of the sample. The majority of respondents (75%) possess more than 5 years of driving experience. Notably, 85% of them reported experiencing an accident within the past year. In terms of fines, 54.5% of the respondents did not encounter any fines in the preceding year. Finally, 37% of the respondents belong to the average-income level.

These insights provide a comprehensive overview of the socioeconomic context within which our study on lane-changing behavior unfolds, offering valuable groundwork for subsequent analyses and interpretations.

Tab. 2 - Frequency analysis of research sample

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 (Million IRR)	Low (≤ 100)	25	20.3
	Average (100 <…≤ 150)	45	36.6
	High (150 <…≤ 200)	31	25.2
	Very high (> 200)	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

Further, we examined the lane-changing behavior of respondents, considering various socioeconomic and driving-related factors (see Figure 4). Notably, gender played a significant role: male drivers exhibited a greater propensity for lane changes compared to the female counterparts, likely due to their higher risk tolerance. Age also influenced lane-changing tendencies. As drivers aged, their willingness to change lanes decreased. This phenomenon may be attributed to older drivers having slower reaction times and a more risk-averse nature. Conversely, as driving experience accumulated, drivers became more inclined toward discretionary lane changes, suggesting increased confidence in their driving abilities.

Interestingly, accident history impacted lane-changing behavior. Drivers who had experienced more accidents were less likely to change lanes. This finding underscores the influence of past negative experiences on driving decisions. In contrast, the relationship between fine experience and lane-changing behavior exhibited a reverse trend. Despite fines being imposed as a deterrent, they did not effectively reduce dangerous driving behaviors. Lastly, education and income levels positively correlated with lane-changing willingness. Higher education and income were associated with a greater propensity for lane changes. These findings highlight the multifaceted factors influencing drivers' decisions regarding lane changes in traffic scenarios.

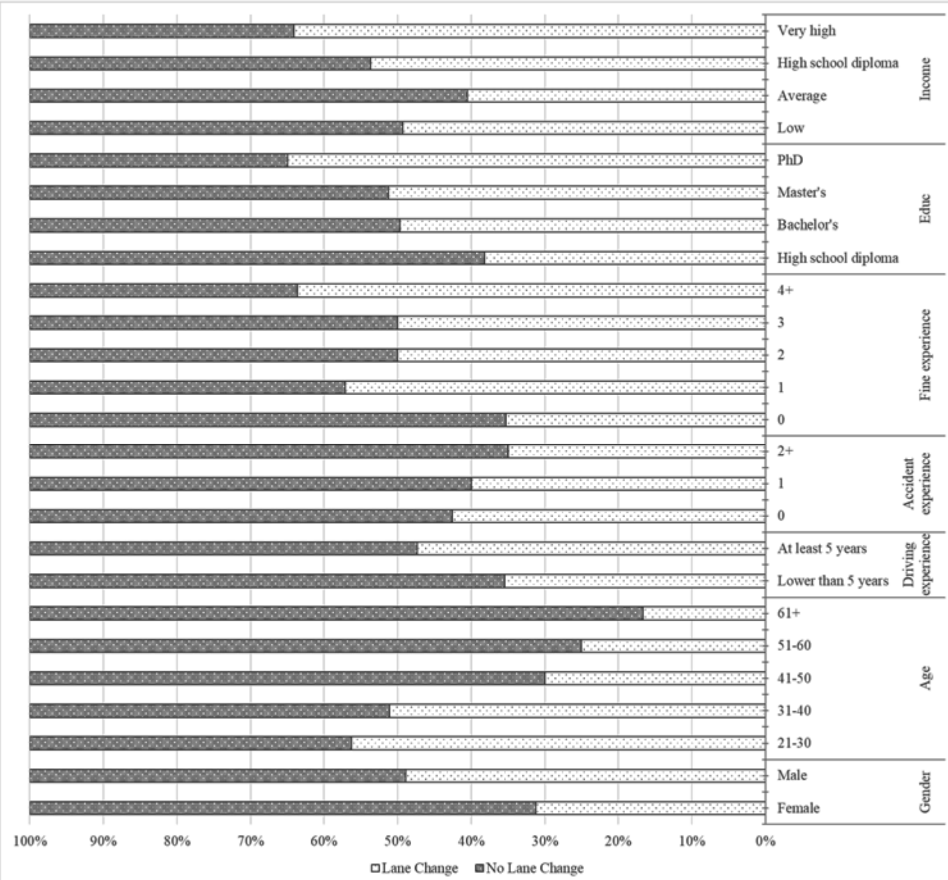

Fig. 4 - Lane-changing propensity based on socioeconomic and driving-related factors

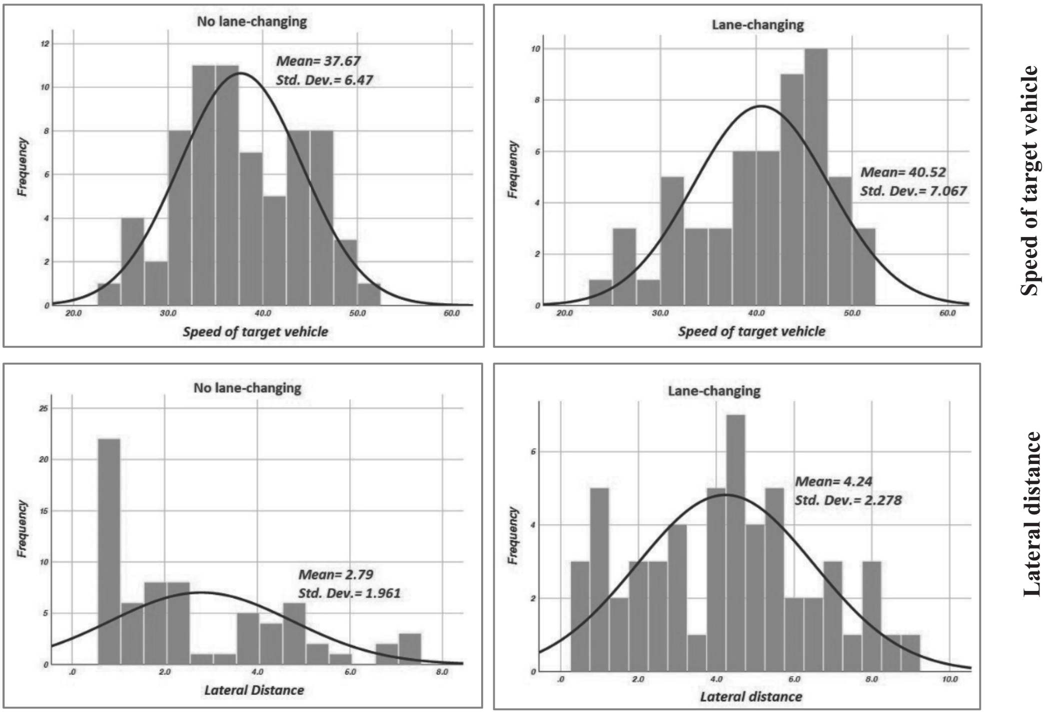

Fig. 5 - Histogram of speed of target vehicle and lateral distance stratified by lane-changing behavior

Further, we have also presented the speed distribution and the lateral gap maintenance of the vehicles which have been classified based on the lane-changing behavior of drivers within the study location (Figure 5). The relationship between speed and lane-changing behavior can be described as directly proportional. As speed increases, drivers may be more inclined to change lanes frequently in order to maintain a desired pace or make progress towards their destination more quickly. Higher speeds can also lead to a faster rate of traffic flow, prompting drivers to adjust their lane position more frequently to navigate through the flow of vehicles effectively. Similarly, the relationship between lateral distance and lane-changing behavior can also be described as directly proportional. When there is ample lateral distance between vehicles, drivers are more likely to change lanes frequently. Conversely, when lateral distance is limited or when drivers feel crowded by nearby vehicles, they are less likely to change lanes in order to create a safer buffer zone around their vehicle.

The relationship between speed and lane-changing behavior can be described as direct, meaning that as speed of target vehicle increases, the likelihood of lane changes tends to decrease. This is because at higher speeds, there is less time and space available for making lane changes safely, so drivers are more likely to maintain their current lane position. On the other hand, the relationship between lateral distance and lane-changing behavior can be described as directly proportional. As the available lateral distance between vehicles decreases, drivers may be more inclined to change lanes in order to create a safer buffer zone around their vehicle. Therefore, when lateral distance is limited, lane-changing behavior is likely to increase as drivers seek to maintain a safe driving environment.

4. Estimation results and discussion

This section presents the outcomes of a binary logit model used to identify the explanatory variables influencing drivers' propensity for lane-changing behavior (Table 3). Our investigation focuses on the impact of driving behavior, attitudinal factors, and socioeconomic characteristics on lane changes in the context of downstream queues. To achieve this, we employed the Nlogit software to estimate a binary logit model. Specifically, we constructed two utility functions—one representing the probability of lane change (LC) and the other representing the probability of no lane change (NLC). It is important to note that due to the iterative nature of modeling, we estimated approximately 300 binary logit models using a stepwise approach. In this iterative process, each variable was individually incorporated into the utility function. Variables demonstrating significant effects with logical signs were retained, while those lacking such impact were excluded from the final model. Upon evaluating the estimated coefficients and the goodness-of-fit coefficient, we draw several conclusions. Firstly, all variables included in the model exhibit logical signs, reinforcing their relevance. Additionally, the likelihood ratio index, which stands at 47.7%, indicates a favorable fit of the model to the research data.

To further evaluate the model's predictive accuracy, we computed the percent-correct criteria. Remarkably, the estimated model achieved an 85.5% accuracy, underscoring its robustness in predicting lane-changing behavior. Our analysis reveals significant factors influencing drivers' lane-changing behavior in the context of queues. Notably, the speed of the target vehicle (VT) emerges as a crucial determinant. A positive association (β: 0.144, p-value = 0.003) indicates that higher target vehicle speeds correlate with an increased likelihood of lane changes. This phenomenon aligns with the nature of discretionary lane-changing, where drivers shift to adjacent lanes to attain their desired speeds. This finding is well-aligned with earlier research by Park et al. [22] and Schmidt et al. [29]. Furthermore, the lateral distance between the target vehicle and the left-side vehicle or obstacle (LATDTLB) significantly impacts lane change utility. With a positive sign and a 1% significance level (β: 0.499, p-value = 0.001), this variable underscores the role of spatial positioning in drivers' decision-making during lane changes. In other words, as this distance increases, the likelihood of lane changes also rises, aligning with prior research by Dilipan et al. [30] and Park et al. [22]. Turning to attitudinal variables, law evasion plays a pivotal role. With a positive coefficient (β: 2.384) and a 1% significance level (p-value: 0.006), this variable indicates that heightened law evasion corresponds to an increased propensity for lane changes during queue encounters. Drivers inclined toward evading traffic regulations are more likely to switch lanes to avoid slower-moving vehicles. Additionally, the behavior of individuals at intersections lacking traffic violation cameras during yellow lights (YELOW5) significantly influences lane-changing behavior. The positive coefficient (β: 3.353) at a 10% significance level (p-value: 0.065) underscores the impact of intersection-related decisions on drivers' lane-changing choices. In other words, individuals habitually passing through yellow lights at intersections lacking cameras exhibit a heightened inclination toward lane changes when encountering traffic. Turning to age-related effects, the estimated coefficient for the AGE41-50 variable (β: −1.568, p-value: 0.035) indicates that individuals aged 41 to 50 years are less disposed to discretionary lane changes compared to their counterparts in other age groups. This phenomenon aligns with prior studies, which attribute this trend to age-related factors such as diminished risk-taking propensity and slower reaction times [31, 32]. Additionally, the NEARLIG1 variable significantly influences lane-changing behavior. With a negative coefficient (β: -1.672) and a 1% significance level (p-value: 0.008), it underscores a reduced likelihood of lane changes when drivers face downstream queues. Drivers who maintain a safe distance from preceding vehicles and refrain from frequent headlight flashing exhibit a more cautious approach in such scenarios.

In contrast, the determinants influencing the propensity for refraining from lane changes can be succinctly summarized as follows. Firstly, the variable denoting drivers who merely execute lane changes, when confronted with pavement damage (referred to as PAVELCNO), exhibits statistical significance with a positive coefficient (β: 1.640) at a 1% significance level (p-value = 0.009). This implies that these individuals, relative to their counterparts, exhibit reduced proclivity for lane changes when confronted with a downstream queue. Secondly, the preceding vehicle speed variable (VL3540) demonstrates a significant positive coefficient at the 5% significance level (β: 1.441, p-value = 0.046) within the context of the non-lane-changing function. Specifically, if the speed of the preceding vehicle falls within the range of 35 to 40 km/h, the likelihood of refraining from lane changes increases. Notably, this finding aligns well with prior investigations conducted by Park et al. [22] and Schmidt et al. [29]. The estimated coefficient of R-OVERT, which represents drivers who infrequently move to the right shoulder of the road during traffic congestion, has been found to be significantly associated with the probability of not changing lanes when confronted with a queue. Specifically, the coefficient of RGAV2 is positive (β RGAV2 = 2.608) and statistically significant (P-value = 0.007) in the utility function modeling non-lane-changing behavior. This implies that individuals exhibiting this behavior are more likely to maintain their lane when faced with a queue. Furthermore, the significant coefficient of LATDTRB (lateral distance between the target vehicle and the right-side obstacle in zone B) is negative (β: -0.220, p-value = 0.020). This finding indicates 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 encountering a queue decreases. These results align with previous studies by Dilipan et al. [30] and Park et al. [22]. Additionally, the coefficient of the ACCEXP2 variable reveals that being a driver who has experienced at least two accidents in the past year is negatively associated with the likelihood of non-lane-changing behavior (β: -4.656, p-value: 0.024). This coefficient is statistically significant at a 5% level, suggesting that individuals who have encountered two accidents in the past year are more inclined to change lanes when faced with a queue.

We have used marginal effects as a valuable tool for identifying the pivotal factors that influence such behavior. These effects quantify the change in the probability of selecting the dependent variable in response to a one-unit change in an independent variable, while keeping all other variables constant. For instance, consider the impact of increasing the target vehicle's speed by 1 kilometer per hour. This modest acceleration corresponds to a 1.8% increase in the likelihood of lane changes. Notably, dummy variables—such as the age group denoted by Age 4150—yield intriguing insights. Belonging to this specific age category, relative to other age groups, leads to an approximately 20% reduction in the propensity for lane changes. Delving deeper into the findings, we discern that certain behaviors significantly influence lane-changing tendencies. Law-evading and the act of crossing yellow lights at intersections without violation recording cameras emerge as the most influential factors that elevate the likelihood of lane changes. Conversely, the pivotal factor associated with non-lane-changing behavior pertains to individuals who infrequently shift to the right side of the road (right shoulder) when confronted with downstream congestion. These insights contribute to our understanding of driver behavior and have implications for traffic management and safety measures.

Tab. 3 - Estimation result of binary logit model regarding the lane-changing decision

Definition	Coefficient	t-stat	Marginal effect
Doing a discretionary lane change utility function			
Alternative-specific constant	− 10.132***	− 3.47	-
Speed of target vehicle	0.144***	2.97	0.0182
Lateral Distance of Target Vehicle from Left obstacle or car at Zone B	0.499***	3.23	0.0630
If driver's age is between 41 and 50 years old=1, otherwise=0	− 1.568**	− 2.11	− 0.1982
Being a law-evading driver	2.384***	2.75	0.3014
Drivers who consistently maintain a safe distance from the preceding vehicle and refrain from frequently flashing their headlights	− 1.672***	− 2.65	− 0.2114
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			
Drivers who merely change lanes when faced with pavement damage.	1.639***	2.61	0.1762
Lateral Distance of Target Vehicle from right obstacle or car at Zone B	− 0.220***	− 2.33	− 0.0237
If the speed of preceding vehicle between 35 and 40 km/h= 1; otherwise= 0	1.441**	2.00	0.1548
If a driver experienced at least 2 accidents in last year= 1; otherwise= 0	− 4.656**	− 2.25	− 0.5003
If a driver rarely moves 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		
$\mathbf{LL(\beta)}$	− 44.966		
$\mathbf{LL(C)}$	− 85.158		
$\mathbf{LL(0)}$	− 85.950		
$\boldsymbol{\rho_C^2}$	0.472		
$\boldsymbol{\rho_0^2}$	0.477		

Our DLC model is beneficial for various purposes related to traffic flow analysis, transportation planning, and traffic management. It can help in understanding and predicting how vehicles change lanes on highways which is essential for optimizing traffic flow, improving safety, and reducing congestion. In a more-detailed explanation, transportation engineers and planners can use the model to assess the impact of lane changes on traffic flow and capacity. Further, traffic management authorities can leverage lane-changing models to analyze and implement strategies for reducing bottlenecks, optimizing lane utilization, and enhancing overall traffic operations. By calibrating these models with real-time data from traffic sensors and cameras, authorities can make informed decisions to improve traffic flow in urban areas. In terms of calibration and theoretical development, the model typically calibrated and validated using empirical data collected from field observations or simulation experiments. Parameters such as driver behavior, vehicle dynamics, road geometry, and traffic conditions are incorporated into these models to improve their accuracy and reliability.

5. Conclusions

Over the course of several years, the phenomenon of discretionary lane-changing has been the subject of extensive investigation within the field of traffic flow. Existing research predominantly focused solely on traffic environment characteristics, but a more comprehensive approach is adopted in this study. Specifically, we consider not only the traffic context but also socioeconomic and driving style characteristics. Our analysis is based on data collected from discretionary lane-changing in Tehran, Iran, a densely populated capital city in a developing nation. To model the decision-making process behind lane changes, we employed a binary logit model. The estimation results highlight several key findings:

Positive Associations:
- Speed of Target Vehicle: Drivers are more likely to change lanes when the target vehicle is traveling at a higher speed.
- Law-Evading Behavior: Drivers who exhibit law-evading tendencies (e.g., disregarding yellow traffic signals at intersections) are positively associated with lane changes.
- Lateral Distance: A smaller lateral distance between the target vehicle and adjacent cars increases the likelihood of lane-changing.
- Accident Experience: Drivers who have encountered at least two accidents are more prone to lane changes when faced with a downstream queue.

Negative Associations:
- Older Drivers: Older drivers are less likely to change lanes.
- Following Distance: Drivers who maintain a greater following distance from the preceding vehicle are less inclined to change lanes.
- Pavement Damage: Those who only alter lanes in response to pavement damage exhibit a reduced likelihood of lane-changing.
- Preceding Vehicle Speed: Lane changes are less frequent when the preceding vehicle's speed falls within the 35 to 40 km/hr range.
- Right-Shoulder Usage: Drivers who infrequently use the right side of the road during traffic congestion are less likely to change lanes.

6. Limitations and suggestions for further research

This research has bridged some existing gaps in the literature on discretionary lane-changing behavior. Although it sheds new light on the subject, the study’s limitations have also led to new questions that merit additional investigation. Conducted in a densely populated and polluted urban setting, the findings are not universally applicable due to varying travel behaviors, cultural differences, and environmental conditions. Moreover, the binary logit model employed in this study does not account for the diversity in drivers’ behaviors.

In conclusion, our study has yielded valuable insights into the determinants influencing the likelihood of lane-changing, which can significantly contribute to future research endeavors. Several promising avenues for further investigation emerge from our findings.

Firstly, it is advisable to explore the impact of information availability related to road conditions, lighting, and weather on lane-changing behavior. By incorporating such contextual factors, we can enhance the robustness of statistical models.

Secondly, a fruitful direction involves directly accounting for vehicle and driver heterogeneity in our modeling approach. Expanding our dataset to include a diverse range of vehicles will allow us to capture the nuanced preferences and behaviors of different driver types.

Lastly, the issue of transferability warrants attention. To assess whether our model estimation results hold across different spatial contexts, we can compare lane-changing patterns from the same location at varying time points. Additionally, analyzing data from the same location over different time periods will reveal whether lane-changing behavior remains stable or if it adapts in response to evolving vehicle technologies and other external factors. These investigations will enhance our understanding of driver behavior in dynamic traffic environments.

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