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Research Article

Effects of Rightmost Lane Avoidance Phenomenon on Road Performance and Safety: A Case Study in Türkiye

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Abstract
The lane selection tendencies of drivers and vehicle distribution across lanes on multi-lane highways significantly influence road performance and safety. This study investigates the "Rightmost Lane Avoidance Phenomenon" (RLAP), a common traffic behavior on multi-lane highways in Turkey, and evaluates its impact on road efficiency and safety. Traffic data were collected from a highway section where RLAP is prevalent, and analyzes were conducted using a calibrated SUMO (Simulation of Urban Mobility) microsimulation model. Key performance indicators included vehicle delays and lane-specific traffic density, while safety was assessed using surrogate safety measures like "Time to Collision." The results reveal that RLAP severely affects road performance and safety, with the phenomenon increasing the risk of safety-critical incidents nearly fourfold compared to ideal conditions. Among vehicle types, passenger cars and buses traveling at higher speeds are disproportionately impacted. This study is the first to comprehensively analyze RLAP, emphasizing its adverse consequences on road networks. Findings provide critical insights into the challenges posed by RLAP and highlight the need for targeted strategies to mitigate its effects. The study lays a foundation for future research aimed at understanding and addressing RLAP, contributing to enhanced traffic management and improved road safety outcomes.

Keywords
Lane utilization, Road safety, Multi-lane highways, SUMO, Simulation, Turkiye.

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1. Introduction

The concept of Ideal Lane Choice Behavior (ILCB) defines the positioning of vehicles in the appropriate lane after completed overtaking maneuvers, commonly known as the “keep right except to pass” rule. The implementation of this rule leads to a distribution of traffic flow among lanes according to vehicle speed, which leads to positive results in terms of road performance in light traffic conditions (Yang & Nie, 2016) and safety (Gao et al., 2018). Factors contributing to deviations from the ILCB include heavy vehicle density, average speeds on road segments, traffic rules, road surface conditions, and vehicle composition ratio, which affect drivers' lane preferences (Yousif et al., 2013). However, on multi-lane highways in Turkey, especially in situations where the number of passenger cars outweighs heavy truck traffic and appropriate lanes are free, there is a tendency for drivers to avoid the rightmost lane, commonly referred to as the rightmost lane becomes. This tendency has become widespread among drivers in recent years and has evolved into a phenomenon referred to in this study as the “Rightmost Lane Avoidance Phenomenon” (RLAP). This issue has also been addressed by official authorities. According to Article 46/2-e of the Highway Traffic Law, as of 2025, drivers who unnecessarily occupy lanes other than the rightmost lane on highways will be subject to an administrative fine of 4,152 TL.

The term “lane utilization” refers to the distribution of traffic flow among appropriate lanes (Transportation Research Board (TRB), 2000), and within this framework, the right lane avoidance (RLAP) phenomenon can be evaluated. Mahalel and Hakkert examined studies on lane usage and reported that the increase in traffic flow on multi-lane highways could lead to safety issues as usage shifts from the rightmost lane to the middle lane (Mahalel & Hakkert, 1983). A study in France examined the impact of control measures such as variable speed limits on lane usage (Duret et al., 2012). In the United Kingdom, the distribution of heavy goods vehicles in motorway lanes has been studied and modeled (Yousif et al., 2013). In general, these studies focused on modeling lane usage factors associated with increased traffic flow. Lane utilization ratio is defined as the ratio of traffic flow in a lane to the total traffic flow through a road section (Heidemann, 1994; Wu, 2005). A study in Italy examined lane utilization on highways and compared them in different countries, including Turkey (Pompigna & Rupi, 2017). The results of this study suggest that drivers in Turkey tend to avoid the rightmost lane even when traffic volume is low, unlike other countries where the rightmost lane is widely used when traffic volume is low. In addition to these studies, research often focuses on modeling lane usage distribution (Golias & Tsamboulas, 1995; Kurle et al., 2016; J. Lee & Park, 2011; Sasahara et al., 2020).

Studies focusing specifically on lane use in Turkey are limited. In a study comparing lane usage in multilane traffic conditions in Turkey with those in developed countries, Günay found that the middle lane was used significantly more frequently than the rightmost lane, even under free-flow conditions (Gunay, 2004). This finding supports the existence of the far-right lane avoidance phenomenon proposed in this study. In addition, Günay conducted studies on modeling lane discipline using traffic data from Turkey and various other countries (Gunay, 2009; Gunay, 2003). Similarly, Aydın and Topal analyzed the effects of road surface deformations on lane usage based on observations on a two-lane road section in Turkey (Mutlu Aydin & Topal, 2016). In this context, there is no comprehensive study in the existing literature that quantitatively evaluates the effects of the RLAP phenomenon on traffic safety and performance; in this respect, the study constitutes one of the first attempts to examine the issue in depth.

Despite the limited number of studies on unique traffic phenomena such as RLAP (Rightmost Lane Avoidance Phenomenon), it is obvious that these phenomena manifest themselves in different forms around the world. For example, a phenomenon observed on Chinese highways and described by (Fu et al., 2006) as “heavy vehicles and cars in different lanes” has similarities with the RLAP observed in Turkey. The main causes of this phenomenon include the presence of different types of vehicles and a large number of vehicles, especially the high presence of heavy trucks. However, whether this phenomenon is observed in situations with low traffic density and low proportion of heavy trucks, as reported in Turkey, remains unclear. Conversely, a similar traffic phenomenon has been reported on multi-lane roads in India (Shirke et al., 2019), where researchers pointed out lack of lane discipline, freedom of choice and heterogeneity in Indian traffic. In this context, it is emphasized that instead of relying on lane behavior models developed for developed countries, specific models need to be developed for countries such as India with special traffic conditions. These two studies show that unique traffic phenomena such as RLAP are not only limited to Turkey but can occur in different countries for different reasons and in different forms. Deepening the understanding of these phenomena is crucial for managing traffic flow and improving road safety. In particular, the observation of RLAP even under free traffic conditions suggests that this phenomenon is closely related not only to traffic density or vehicle types, but also to driver behavior and traffic culture. Therefore, comprehensive studies are needed to understand the effects of RLAP and similar phenomena and to develop effective intervention strategies.

Over the last decade, Turkiye has made significant investments in its highways, converting a significant portion of its state highways into dual carriageways with multiple lanes. However, after this transformation, RLAP was frequently observed on multi-lane road sections. These multi-lane roads, which are primarily designed to increase capacity, are expected to face capacity and safety issues due to RLAP. In this context, the research question is defined as follows: “To what extent does RLAP affect the performance and safety of highways?” To clearly answer this question, the following objectives were identified:

1. Analysis of traffic and speed data collected for different vehicle types on a road section where RLAP is frequently observed.
2. Building a simulation setup for ILCB and RLAP for the relevant highway section.
3. Statistical examination of the effects of RLAP.
4. Detailed analysis of the results achieved in terms of traffic safety and performance

Successful achievement of the above objectives will enable a more detailed study of the impact of RLAP on road performance and safety, which will lead to a clearer understanding of this phenomenon and contribute to the adoption of necessary measures.
In the following sections of this study, definitions of ILCB and RLAP are first provided. The methodology section explains the techniques used to detect, analyze and compare the effects of RLAP and ILCB. The insights gained from the analyzes are presented in the Results section using various clear figures and tables. Finally, in the discussion and conclusion section, the insights gained are discussed and further research directions are suggested.

Symbols and Abbreviations

PC	Passenger Car
CV	Light Commercial Vehicle
FPC	Fast Passenger Car
MPC	Medium Passenger Car
SPC	Slow Passenger Car
RLAP	Rightmost Lane Avoidance Phenomenon
ILCB	Ideal Lane Choice Behavior
SUMO	Simulation of Urban Mobility
TRB	Transportation Research Board
TGDH	Turkish General Directorate of Highways
TTC	Time to Collision
LI	Lane Index
N_1, N_2	The number of data points used for ILCB and RLAP
x_1, x_2	The average metric value for ILCB and RLAP
s_1, s_2	The standard deviation of the metric for ILCB and RLAP
p	"p" value for hypothesis test
h	h=0: Accept the null hypothesis h=1 : Reject null hypothesis
v_s	Speed of the subject vehicle
v_f	Speed of the front vehicle
v_L	Speed of the leading vehicle ahead of the front vehicle

1.1. Ideal Lane Choice Behavior (ILCB)

Ideal Lane Choice Behavior (ILCB) can be defined as the driver's tendency to drive in the lane corresponding to his speed on multi-lane highways and to use the adjacent faster lane to overtake a slower vehicle in his lane and then return to the lane corresponding lane. To express this behavior mathematically, consider a multi-lane highway with continuous traffic flow where the lane index value LI is defined for lane (i). Let v_s be the speed of the subject vehicle traveling on the lane (i). Suppose there is a front vehicle traveling in front of the subject vehicle at a speed of vf and a lead vehicle traveling in front of the leading vehicle at a speed of vL. The graphical expression of the positions of these vehicles is given in Equation 1. Under these conditions, the ILCB for the vehicle in question can be defined as given in Equation 1.

$$ILCB_{subject_{veh}} = \begin{cases} LI^1(i), LI^2(i),\ LI^3(i) & \leftarrow v_s \le v_f \quad (I) \\ LI^1(i), LI^2(i+1), LI^3(i) & \leftarrow v_s > v_f \ and\ v_s \le v_L \quad (II) \\ LI^1(i), LI^2(i+1),\ LI^3(i+1),\ LI^4(i+1) & \leftarrow v_s > v_f \ and\ v_s > v_L \quad (III) \end{cases} \tag{1}$$

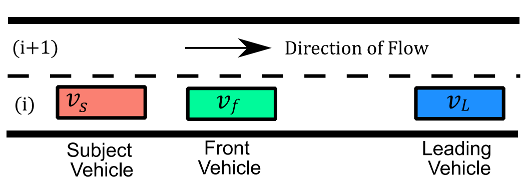

Figure 1. The graphical expression of the vehicle's positions.

In Equation 1, the exponential expression of LI, ranging from 1 to 3, denotes the maneuver steps. For instance, the term $LI^2(i+1)$) represents the index of the first adjacent lane faster than the travel lane (i) in the subject vehicle's lane choice at step 2. In scenario (I), no lane change maneuver occurs when the speed of the subject vehicle is less than or equal to that of the front vehicle. Maneuvers occur in Scenarios (II) and (III). In Scenario II, since the speed of the subject vehicle is higher than that of the front vehicle, in the second maneuver step (LI^2), the subject vehicle overtakes the front vehicle by occupying the lane indexed as *(i+1)*. However, since the speed of the subject vehicle is lower than that of the leading vehicle, in the third maneuver step (LI^3), it returns to the lane indexed as *(i)*. In Scenario III, since the speed of the subject vehicle is higher than both the front and leading vehicles, it overtakes the front and leading vehicles by occupying the lane indexed as *(i+1)*, and in the final maneuver step (LI^4), it returns to the lane indexed as *(i)*.

1.2. Rightmost lane Avoidance Phenomenon (RLAP)

For effective road use, compliance with geometric design and construction procedures that are suitable for driving dynamics is crucial (Kim & Ferris, 2024). Additionally, drivers are expected to adhere to set rules to ensure safety and smooth traffic flow. Ideally, vehicles on multi-lane highways should use lanes appropriate to their speed to effectively utilize road capacity. Deviations from ideal driver behavior can have a negative impact on capacity and safety (Y.-C. Lee et al., 2023; Zhang et al., 2023).

In countries where the majority of goods are transported by road, the rightmost lane is often occupied by heavy goods traffic. Consequently, passenger cars seeking a relatively higher cruising speed may not be able to travel at the desired speed if they are forced to travel in the right lane when heavy vehicles are present. This situation often leads to frequent deceleration and acceleration maneuvers. Additionally, driving in close proximity to larger vehicles can have negative impacts on drivers due to safety and comfort concerns.

The right lane avoidance (RLAP) phenomenon explained in this study describes the avoidance of using the rightmost lane even when traffic with heavy vehicles is at an appropriate level and there are appropriate traffic flow conditions for using the rightmost lane. This behavior is a common trend, particularly among car drivers. In a study conducted by Pompigna et al., it was found that the usage of rightmost lanes on multi-lane highways in Turkey is lower compared to other countries even at low traffic volumes (Pompigna & Rupi, 2017). This situation is clear evidence of the existence of RLAP. But Fu et al. did not particularly address how common this behavior is among drivers.

Using satellite imagery, it has become possible to capture vehicle lane usage patterns to a certain extent (Umamaheswari & Avanija, 2024). While this method only provides snapshots, it offers the advantage of examining long stretches of road simultaneously and contributes significantly to identifying the RLAP. In this study, Google Earth images from the study area and specific points are presented in Figure 2. The vehicles marked with a red box, even though the rightmost lane is suitable for traffic (i=1), still occupy lanes marked as (i=2) (middle lane) or (i=3) (middle lane). are marked. Of the 35 vehicles shown in the images, 33 that avoid the rightmost lane despite their suitability clearly show the RLAP. When examined using this method, many intercity and multi-lane roads in Turkey also exhibit RLAP.

Figure 2. Satellite images related to the Rightmost Lane Avoidance Phenomenon

To explain RLAP mathematically, let's refocus on the lane-changing maneuver defined in the ILCB section. In situations where RLAP is applied to driver behavior, the lane-changing behavior of the subject vehicle can be defined as stated in Equation 2.

$$RLAP_{subjectVeh} = \begin{cases} LI^1(i), LI^2(i),\ LI^3(i) & \leftarrow [v_s \le v_f \wedge i > 1\ ] \quad (I) \\ LI^1(i), \quad LI^2(i+1),\ LI^3(i) & \leftarrow [v_s > v_f \wedge v_s \le v_L \wedge i > 1]\ (II) \\ LI^1(i), \quad LI^2(i+1),\ LI^3(i+1) & \leftarrow [v_s > v_f \wedge\ v_s > v_L \wedge i > 1]\ (III) \end{cases} \tag{2}$$

Under the RLAP condition described in Equation 2, the lane-changing behavior is fundamentally similar to that in ILCB, except that the subject vehicle prefers lanes other than the rightmost lane $(i = 1)$. This results in passenger vehicles avoiding the use of the rightmost lane except for exit and entry maneuvers. This avoidance behavior is expressed in Equation 2 as $(i > 1)$.

2. Methodology

The simulation model of the road section under consideration was created using the SUMO traffic simulator. SUMO is a microscopic simulation model that can successfully model various traffic conditions and is often preferred in literature due to its free, open-source nature (Lopez et al., 2018). To model the road network, the OSM Web Wizard application (SUMO sub-app) was used, which converts geographical information obtained from OpenStreetMap into a network file. Then, the speed and traffic information obtained from the Turkiye General Directorate of Highways (TGDH) was processed using the techniques described in Section 2.3 and integrated into the model. After calibrating the microsimulation, the simulation model was run several times, and the results were analyzed. The effects of RLAP conditions were compared in detail to ILCB, with results including average deceleration per vehicle, lane densities and time to collision (TTC). The following sections explain these processes in detail and provide the necessary information.

2.1. Study Site and The Data

The study was carried out on the D200 highway (section 13), which connects the Ankara (Capital city) with the eastern and northern regions. This road is an important route connecting Ankara with the Eastern Anatolia and Black Sea regions. The length of the examined section is approximately 22 kilometers and lies in a west-east direction. The starting coordinates are 39.927453 latitude and 33.006200 longitude, while the ending coordinates are 39.920502 latitude and 33.221086 longitude. The section along the road is completely three-lane, and in some places there are various ground-level connections. The intersections formed at these junctions are typically T-shaped and controlled by secondary level controls (yield or stop signs). In addition, there are gas stations directly connected to the main road and located right next to it along the road.

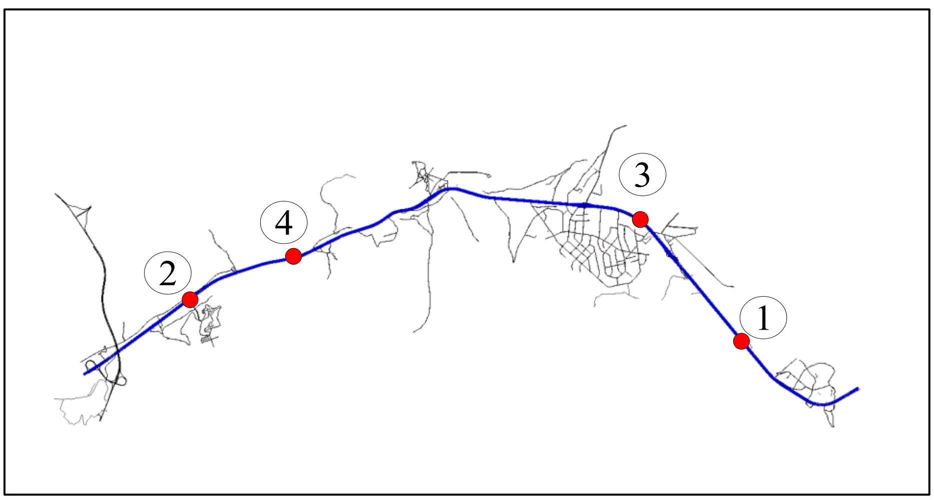

Figure 3. General view of the road section modeled in this study (The numbers refer to the image numbers in Figure 2)

Traffic volume and speed data were obtained from counting stations owned by the TGDH. The dataset includes hourly average volume and speed information for five different vehicle types: Passenger Cars (PC), Light Commercial Vehicles (CV), Buses, Trucks, and Truck+SemiTrailer, between January 1, 2023, and December 8, 2023. These data sets contain volume values for vehicles traveling only on main roads, and volumes of vehicles joining the road have not been considered in this study, as it would complicate the detection of the RLAP condition effect.

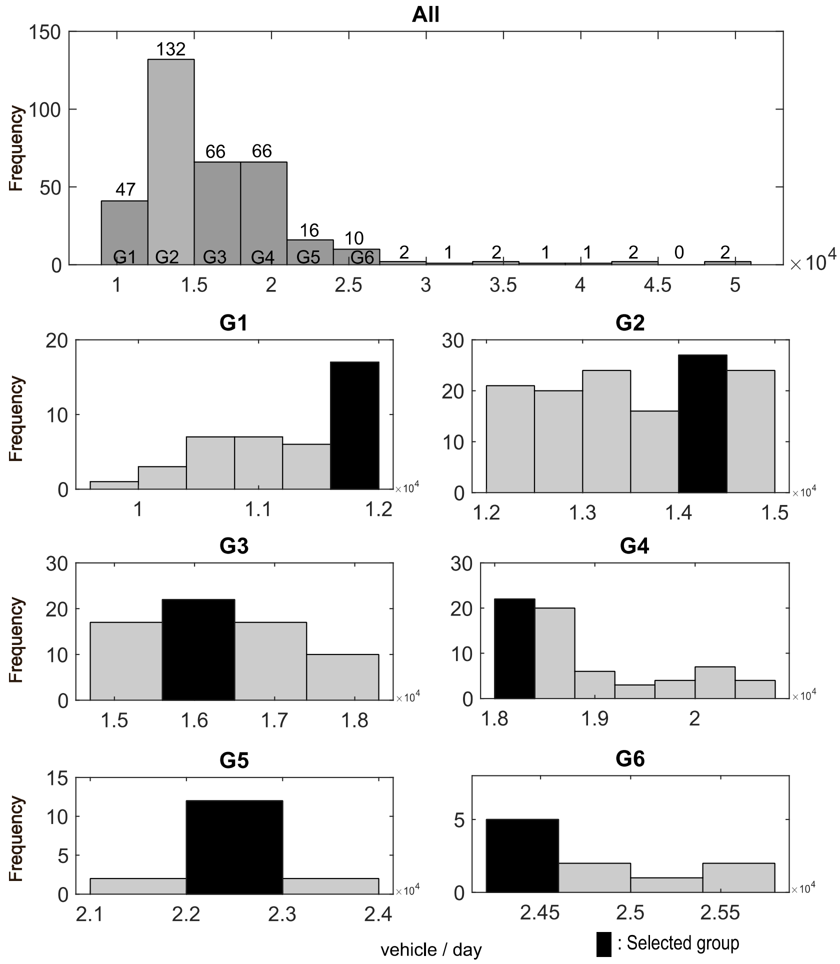

Figure 4. Histograms used for determining traffic groups

2.2. Selection of Traffic Groups

To investigate the impact of RLAP on performance and safety, the goal was to identify the most commonly observed traffic conditions on this road section and generate these conditions in a simulation environment. To achieve this goal, groups with a high frequency in the data set were first identified. From Figure 4, which shows the distribution of total daily vehicle counts for all vehicle types, it can be seen that the most common daily traffic conditions occur on Group 2 (G2) days. Additionally, it can be seen from Figure 4a that the number of days with a daily traffic volume exceeding $3x10^4$ vehicles/day is quite low (only observed 1 or 2 times), indicating that these are rare occurrences. In addition, it can be observed that the traffic volume is rarely more than 3x104 vehicles/day. Looking at the dates of these unusual days, it is known that they fall on official or religious holidays and the movement of heavy vehicles on these days is restricted by the relevant authorities. Since all lanes must be used on busy days, it was decided not to use unusual days for the RLAP analysis. Therefore, the first 6 of the 14 total groups that appeared in Figure 4 (All) were selected for analysis. The groups were then reclassified to determine the days representing each group, and the distributions under the corresponding title are shown in Figure 4. Finally, the traffic conditions of the days with the highest total traffic volume within the most frequently observed area in the groups were used to represent each group.

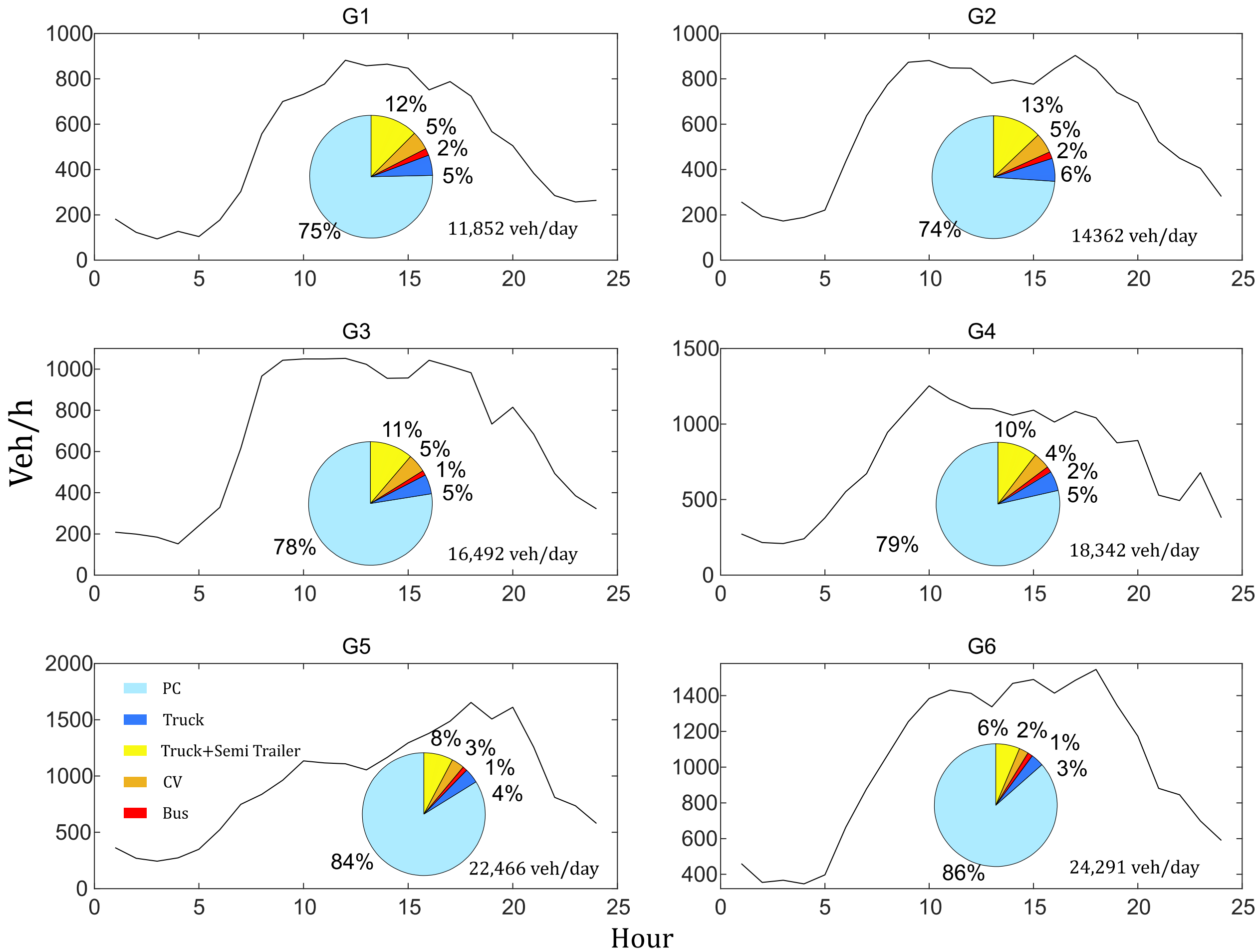

Figure 5. Hourly traffic volume profiles and vehicle type distributions for days representing traffic groups

The days that represent each traffic group are referred to below by their group names. The traffic conditions for these groups are shown in Figure 5. Unlike the two-peak hourly traffic flow profiles we typically see, different profiles were observed in this study. Since this is an interstate road, weather conditions and other factors make sense that profiles would arise that are different from the two peak points observed on city roads. From G1 to G6, an increase in total daily vehicle traffic is observed. This increase in daily vehicle traffic is a significant factor influencing driver behavior.

If you look at the distribution of vehicle types, you can see that passenger cars (PCs) make up the clear majority; Truck+SemiTrailer heavy-duty vehicles are the second most frequently observed vehicle type after PCs. Trucks came in third place, while buses were identified as the vehicle type with the lowest rate.

Due to the different speed distributions of vehicle types, speed measurements were obtained for each vehicle type from the TGDH. The data obtained from the TGDH counting stations is compiled as hourly averages and made available to researchers. The speed distribution of the PC has been treated differently than other vehicle types and will be discussed in detail in later sections.

SUMO can generate vehicle speed distributions according to a normal distribution on demand, enabling a more accurate approximation of observations. However, when a normal distribution is used, the speeds of vehicles at the tail of the distribution, and therefore of vehicles with very low or very high speeds, can reach unrealistically low values such as 0 km/h. To prevent such unrealistic results, lower and upper bounds (c_L, c_U) are used. Speeds outside these values are adjusted to the limit values. The specific speed distributions for vehicle types and the c_L and c_U values are shown in Figure 6.

The c_L and c_U values were determined using Q-Q plots to establish the appropriate limits of speed distributions for a normal distribution. When examining the Q-Q plots specific to vehicle types from Figure 6, it is observed that speeds are consistent with a Gaussian distribution within the range of [-2σ, +2σ]. Based on this finding, the c_L and c_U values for each vehicle type are identified in Figure 6, indicated by vertical lines on the speed distributions.

Compared to other types of vehicles, the PC can reach higher speeds and have higher acceleration rates. This makes PC the vehicle type that most avoids the right lane in traffic flow. Additionally, because they account for the highest proportion of the vehicle count distribution, they exhibit greater diversity in terms of driver types and behavior. Therefore, PCs in simulations are modeled as three sub-vehicle types based on their speed: Fast PC (FPC), Medium PC (MPC), and Slow PC (SPC). The procedure for determining the sub-vehicle types is shown in detail in Figure 7.

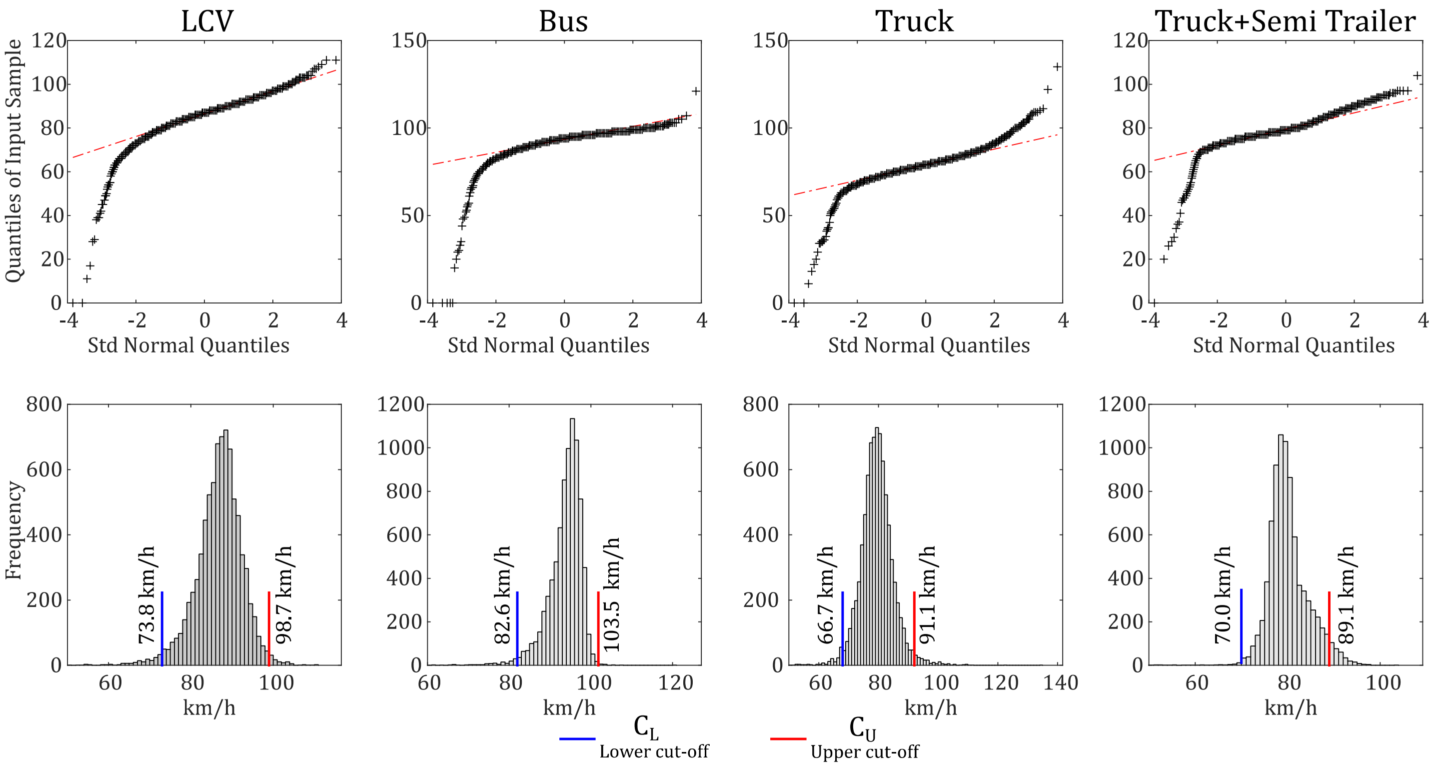

Figure 6. Speed distribution by vehicle types and determination of cut-off values using Q-Q plots

A Q-Q plot is used graphically to test how well a data set fits a normal distribution (Habibzadeh, 2024). From the Q-Q chart prepared for the speed values of PCs, the data is normally distributed within the range of [-1.5σ, +1.5σ] and deviates from normal distribution beyond ±2σ. Despite the deviation from normal distribution outside the range indicated in the Q-Q plot, examination of the histogram in Figure 7 leads to the conclusion that these ranges could also correspond to a normal distribution. Given this insight, PC speeds are divided into three ranges: SPC, MPC and FPC. The region with ±σ from the mean is considered as MPC, and the regions with ±3σ from the mean are considered as regions of extreme behavior. The negative area is referred to as SPC, the positive area as FPC. The limits defined by ±σ and ±3σ are used as c_L and c_U to model the speed distributions of PCs. These limits can be seen in the histogram in Figure 7.

2.3. Microscopic Model Parameters and Calibration

After creating the road network and integrating traffic flows based on vehicle types into the simulation model, lanes in the road network were adjusted depending on vehicle type to model the behavior of vehicles under ILCB and RLAP conditions. While under the LCB condition, passenger vehicles (PC) are allowed to use the rightmost lane, the rightmost lane is restricted for PC vehicles except for entry and exit to simulate the RLAP condition. In contrast, under the ILCB condition, no such restriction was applied, allowing SPC (Slow Passenger Car) vehicles or some MPC (Medium Passenger Car) vehicles traveling at low speed to use the rightmost lane.

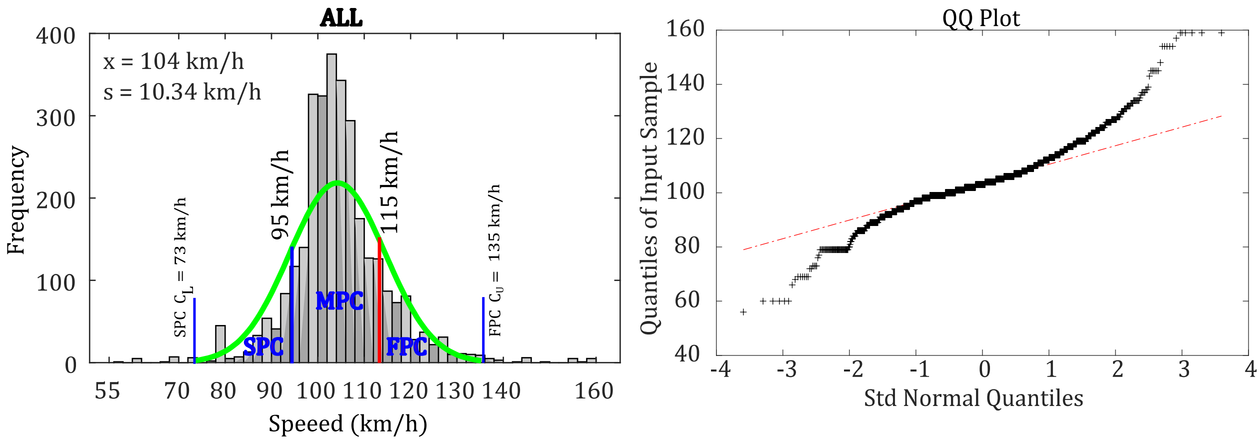

Figure 7. Subgrouping for passenger cars and speed distribution parameters

The widely accepted Krauss model was chosen as the successor model (Krauß, 1998). The Krauss model is based on the principle that a safe minimum distance from the vehicle in front is maintained using tau (time distance) and reaction times and when the vehicle in front brakes, the vehicle behind also brakes to maintain this minimum distance. Since driver reaction time is generally assumed to be 1 s on average, a value of 1 s was assumed for Tau and driver reaction time in this study. The lane change model has a more complex structure compared to the vehicle following model and is expressed in SUMO with more parameters than the car following model. Default parameter values from SUMO were used for the lane change model (LCM).

Geoffrey E. Havers (GEH) statistics were used to calibrate the simulation model. The GEH statistics are calculated by comparing the traffic volume generated by the simulation model with the traffic volume observed in reality using a specific equation. If the GEH statistic is less than 5, it is concluded that the model is calibrated (Paz et al., 2015). This method is used as a measure of how well the model matches real data.

In this case, “m” represents the observed hourly traffic volume in the field, while “c” represents the hourly traffic volume determined from the simulation. The averages of hourly GEH values obtained on transport group-specific days were calculated and these values are presented in Table 1. The results obtained show that the condition GEH<5 is satisfied for days representing all traffic groups, with values close to 0 for all groups except G3. Based on these results, it is concluded that the model is suitable for analysis.

$$\boldsymbol{GEH = \sqrt{\frac{2(m-c)^2}{m+c}}} \tag{3}$$

Table 1. GEH values for traffic groups.

	G1	G2	G3	G4	G5	G6
GEH	0.94	0.82	4.11	0.74	0.61	0.69

In order for simulations to accurately reflect real traffic conditions, ensuring the randomness of vehicle arrival intervals is critical. This randomness is typically modeled using specific probability distributions. In this study, vehicle arrival intervals were randomized using the Bernoulli process available in the SUMO simulation tool. The Bernoulli process is based on a series of independent experiments with a certain probability of success and provides a suitable approach for modeling vehicle arrival intervals.

Another factor that plays an important role in accurately reflecting randomness is the use of starting numbers. A seed number is a value used as a starting point in random number generators and is critical for ensuring consistent randomness in simulations. In this study, 10 different seed numbers were used and separate simulations were performed for each seed. For analysis, the average values of the results of these 10 different simulations were calculated.

2.4. Performance and Safety Metrics

Performance Metrics:

The first metric used to analyze the impact of RLAP and ILCB conditions on road performance is the $TimeLoss$ metric, defined as the delay time that occurs when vehicles cannot travel at the desired speed determined by the vehicle type in SUMO depends. Let a specific type of vehicle be observed N times during the simulation process and let the travel time t (s) of any vehicle i on the relevant road section be expressed with the average travel speed v (m/s) and the desired speed v^d (MS). In this case, the average $TimeLoss$ value for this type of vehicle can be calculated using Equation 4.

$$TimeLoss = \frac{\sum_{i=1}^{N} t_i \left(1 - \frac{v_i}{v_i^d}\right)}{N} \quad (4)$$

Another metric used for road performance analysis is lane density distributions (J. Lee & Park, 2012). Given the influence of the RLAP phenomenon on the lane preferences of vehicle types, it is appropriate to examine the distributions of lane densities under RLAP and ILCB conditions. When calculating the lane density distributions, the densities (vehicles/km) for each lane are first calculated using the microsimulation model, taking the traffic groups into account. The density of each trace is then normalized to the total density and expressed as a percentage. This method provides valuable information about the distribution of vehicle types across lanes under different traffic conditions.

Safety Metric:
For the analysis of the safety level, the time to collision (TTC) was selected as a surrogate safety measure. RLAP, in addition to drivers' lane preferences, leads to a concentration of vehicles in certain lanes, leading to the creation of safety-risky situations. Although collision event statistics would provide more meaningful safety metrics for evaluating road segments from a safety perspective, creating the required data set is time-consuming because collision events are rare compared to other events in traffic flow. On the other hand, statistics based on surrogate safety measures rely on vehicle movements and interactions within the traffic flow and allow the creation of the necessary data set for analysis in a shorter time compared to traditional methods based on collision statistics (Amundsen & Hyden, 1977; KRAAY, 1982).

TTC is a surrogate safety measure commonly used as a safety metric, indicating the time it takes for two moving vehicles to collide if they continue their current movements (Vogel, 2003). Situations where the TTC value falls below a certain threshold are considered surrogate events. A high number of surrogate events indicates a high collision risk, while a low TTC value indicates that vehicles are experiencing more serious collisions. The TTC threshold value is preferred to range between 1.5 and 4 seconds in the literature (Mahmud et al., 2019). In this study, the analysis of safety levels for ILCB and RLAP conditions was conducted using the commonly preferred threshold value of 3 seconds.

3. Results

3.1. Road Performance

To determine the impact of RLAP and ILCB on road performance, an analysis of the $\boldsymbol{TimeLoss}$ and lane density distributions was conducted. Firstly, the Wilcoxon rank sum test was used to evaluate the difference in $\boldsymbol{TimeLoss}$ values under RLAP and ILCB conditions. This test is a non-parametric test similar to the Mann-Whitney U-test, that tests the similarity of median values between two independent population samples. This test can be applied even if the two datasets have different numbers of observations. The test results, at the α=0.05 level, are presented in detail for vehicle types and groups in Table 2. The number of data points for all tested datasets for $\boldsymbol{TimeLoss}$ is 240, calculated as 24 hours per-day x 10 seed numbers.

Examining Table 2, it was concluded that vehicle types such as MPC, FPC, LCV and buses rejected the null hypothesis in all transport groups. In other words, for these four vehicle types, preferring the RLAP conditions over the ILCB conditions significantly increased the $TimeLoss$ values for all groups. On the other hand, the Truck+SemiT vehicle type accepted the null hypothesis in all groups. This indicates that the Truck+SemiT vehicle type is the only type not affected by the RLAP conditions. While the vehicle type truck showed no significant difference between traffic groups G1 to G4, a statistically significant difference was observed for G5 and G6. Taking into account the increase in daily traffic volume from G1 to G6, it can be assumed that the RLAP effect for the truck vehicle type will take effect together with the increase in traffic flow. SPC rejected the null hypothesis except for G3 and G4; However, at the current stage of the analysis, no clear connection with the change in daily traffic volume could be determined.

Table 2 The test results are analyzed according to the traffic groups with a significance level of α=0.05

Group	Measure (sec/veh)	Veh. Type	N_1, N_2	x_1	x_2	s_1	s_2	p	h
G1	Time Loss	SPC	240	42.09	41.48	1.66	1.96	<0.05	1
		MPC		35.60	38.11	1.35	4.53	<0.05	1
		FPC		37.19	64.54	5.51	28.87	<0.05	1
		LCV		35.42	35.83	1.58	1.85	<0.05	1
		Bus		31.43	34.68	2.75	5.88	<0.05	1
		Truck		27.22	27.28	0.79	0.95	0.75	0
		Truck-Semi T.		25.95	25.97	0.81	0.82	0.89	0
G2	Time Loss	SPC	240	42.88	42.65	1.69	2.38	<0.05	1
		MPC		36.16	40.26	1.24	4.95	<0.05	1
		FPC		39.50	75.96	5.64	28.97	<0.05	1
		LCV		36.03	36.54	1.47	1.71	<0.05	1
		Bus		32.35	36.52	3.28	6.38	<0.05	1
		Truck		27.50	27.63	0.80	0.92	0.09	0
		Truck-Semi T.		26.31	26.36	0.77	0.82	0.49	0
G3	Time Loss	SPC	240	43.22	43.18	1.75	2.90	0.25	0
		MPC		36.63	42.42	1.67	6.96	<0.05	1
		FPC		43.24	88.20	9.20	38.71	<0.05	1
		LCV		36.23	37.13	1.81	2.37	<0.05	1
		Bus		32.40	37.58	2.77	7.46	<0.05	1
		Truck		27.71	27.86	0.98	1.13	0.22	0
		Truck-Semi T.		26.58	26.68	1.03	1.18	0.51	0
G4	Time Loss	SPC	240	43.59	43.64	1.96	3.24	0.36	0
		MPC		37.09	43.66	1.99	7.49	<0.05	1
		FPC		46.28	95.16	11.36	38.84	<0.05	1
		LCV		36.74	37.51	1.94	2.57	<0.05	1
		Bus		33.84	40.53	3.97	9.64	<0.05	1
		Truck		27.97	28.18	1.12	1.40	0.12	0
		Truck-Semi T.		26.75	26.93	1.12	1.27	0.15	0
G5	Time Loss	SPC	240	44.17	45.81	2.27	4.84	<0.05	1
		MPC		38.01	48.66	2.71	11.29	<0.05	1
		FPC		53.81	116.08	18.36	46.61	<0.05	1
		LCV		37.50	39.05	2.31	3.64	<0.05	1
		Bus		34.97	45.79	4.70	13.13	<0.05	1
		Truck		28.29	28.77	1.25	1.76	<0.05	1
		Truck-Semi T.		27.38	27.63	1.49	1.87	0.41	0
G6	Time Loss	SPC	240	44.16	46.39	2.23	4.83	<0.05	1
		MPC		38.37	50.72	2.66	10.86	<0.05	1
		FPC		56.52	127.17	17.84	44.89	<0.05	1
		LCV		37.58	39.35	2.28	3.63	<0.05	1
		Bus		34.99	45.89	4.20	11.73	<0.05	1
		Truck		28.30	28.80	1.40	1.91	<0.05	1
		Truck-Semi T.		27.30	27.64	1.41	1.76	0.06	0

h=0 : Accept the null hypothesis (No difference between groups), h=1 : Reject null hypothesis (difference between groups), 1,2: Refer to ILCB and RLAP, respectively.

To gain a deeper understanding of the distribution trends of $TimeLoss$ values for vehicle types under RLAP and ILCB conditions, box plots for vehicle types and all traffic groups together are presented in Figure 8. For clarity, passenger cars (SPC, MPC, and FPC) are shown separately in Figure 8-a, while other vehicle types are shown in Figure 8-b.

When analyzing passenger cars, especially in FPCs and under RLAP conditions, it is observed that the $TimeLoss$ values are significantly more widely distributed compared to other types of passenger cars. At first glance, this is a striking finding in Figure 8-a. For FPCs, the interquartile range (IQR) values are found to have a lower limit of approximately 50 seconds per vehicle and an upper limit of approximately 130 seconds per vehicle. This clearly shows that FPCs are exposed to higher $TimeLoss$ values compared to all other vehicle types. Under RLAP conditions, the median value of MPCs is approximately 10 seconds higher per vehicle than the median value under ILCB conditions. While the minimum values are close to each other, Q3 and maximum values are significantly higher when looking at the value distribution. Furthermore, it is observed that under ILCB conditions, the $TimeLoss$ values for MPC vehicles are distributed in a much narrower range.

According to the analysis in Figure 8-b, buses are the most affected by the RLAP conditions among vehicle types other than passenger cars. Under ILCB traffic conditions, buses experience an average delay of 33 seconds per vehicle, while under RLAP conditions this average delay increases to approximately 40 seconds per vehicle, and in some exceptional cases delay times can reach up to 90 seconds per vehicle. For the Light Commercial Vehicle (LCV) vehicle type, it was found that under RLAP conditions the IQR range is higher and wider compared to the ILCB. Although this is not as pronounced as for buses, it does indicate that RLAP conditions may cause further delays in the light commercial vehicle type. The Truck and Truck+SemiT types showed similar distributions under RLAP and ILCB conditions; However, for the truck type, it was observed that the IQR range expanded, and the maximum value was approximately 2 seconds higher per vehicle. The hypothesis results presented in Table 2 also indicate a significant difference for truck type due to the increase in daily traffic, and these results are consistent with each other.

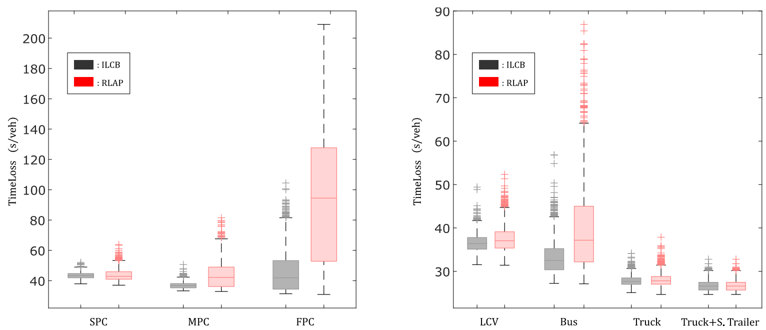

Figure 8. Average time loss for vehicle types under RLAP and ILCB traffic flow conditions

The distribution of lane densities is predicted to be an important factor that can influence the average speed and therefore the performance of the road section. In this context, the density distributions of lanes under RLAP and ILCB conditions were calculated as a percentage by group and are shown in Figure 9. In an overall evaluation, it was found that under ILCB conditions the usage density of lane 1, which is the rightmost lane, varies between 52% and 65%, while under RLAP conditions this ratio is between 14% and 27%. Looking at the increase in daily traffic volume from G1 to G6, it can be observed that with the increase in traffic volume, under both ILCB and RLAP conditions, the proportional usage density of lane 1 decreases. However, a more dramatic decrease is observed under RLAP conditions, with the density ratio for G1 decreasing from 27% to 14%, indicating a more significant decrease compared to ILCB. Consequently, the increase in daily traffic leads to a decrease in the percentage usage of Lane 1, especially under RLAP conditions, in both traffic conditions.

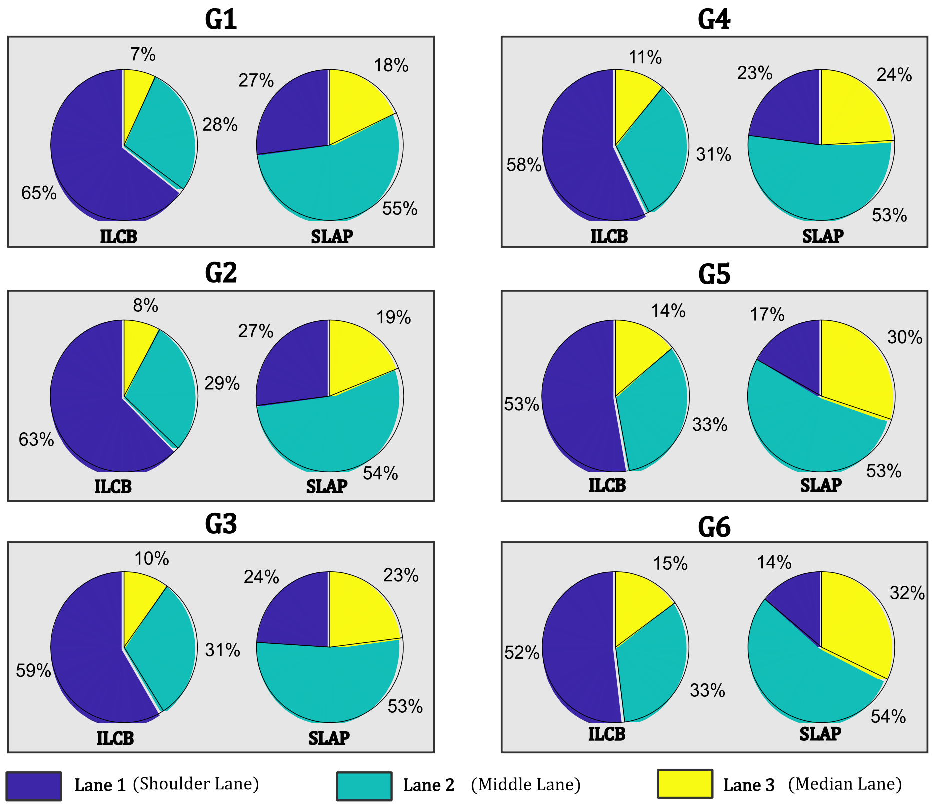

Figure 9. Percentage distribution of lane densities for groups under RLAP and ILCB conditions

According to the analysis shown in Figure 9, the usage percentages of Lane 2, also called the middle lane, vary between 28% and 33% under ILCB conditions, while they range between 53% and 55% under RLAP conditions. This suggests a smaller range of variation compared to other tracks. Under RLAP conditions, it can be observed that a significant proportion of drivers who do not want to drive in the rightmost lane prefer lane 2 in all groups. This observation leads to more than 50% of vehicles choosing lane 2. This observation shows that RLAP conditions increase drivers' tendency to prefer the middle lane when choosing a lane, resulting in a significant increase in the usage density of the middle lane compared to other conditions. This behavioral pattern illustrates how RLAP leads to changes in driver preferences and demonstrates its potential to influence traffic flow.

Lane 3, which is on the far left of the platform, is generally used for overtaking. For lane 3, indicated by the yellow-colored segments in Figure 9, the density percentages under ILCB conditions have the lowest values, ranging between 7% and 15%. However, under RLAP conditions, the utilization rate of lane 3 increased more than twice compared to ILCB conditions. Another important result is that with the increase in daily traffic volume, the usage share of lane 3 approximately doubled from G1 to G6 under both conditions.

3.2. Safety Performance

The simulations conducted to evaluate the RLAP and ILCB conditions for safety include the representative number of incidents for each traffic group and the corresponding TTC values obtained from those incidents. Similar to the parameter $TimeLoss$, the Wilcoxon rank sum test was used to examine the significance of the difference between the two conditions because the TTC values do not follow a normal distribution and the sample sizes are different. This test was carried out with a significance level of α=0.05 and the results are presented in Table 3 for each traffic group separately.

The test results reject the null hypothesis for all traffic groups, indicating a significant difference between the two conditions. Under the RLAP conditions, as shown in Table 3, the mean TTC values (x2) for all groups are lower than the ILCB values (x1). Furthermore, based on the values of N1 and N2, which represent the occurrence of replacement events in the ILCB and RLAP conditions, it can be observed that the probability of occurrence of replacement events in RLAP conditions is about four times higher than that in ILCB conditions. This indicates that RLAP conditions result in a larger number of replacement events and more severe collisions.

Table 3 Wilcoxon rank sum test for TTC (α=0.05)

Group Name	veh/day	Parameter	N_1, N_2	x_1	x_2	s_1	s_2	p	h
G1	11,852	Time To Collision (TTC)	350, 1534	2.88	2.83	0.12	0.16	<0.05	1.00
G2	14,362		588, 2128	2.88	2.82	0.12	0.17	<0.05	1.00
G3	16,492		884, 3332	2.86	2.82	0.13	0.17	<0.05	1.00
G4	18,342		1096, 4220	2.85	2.82	0.15	0.17	<0.05	1.00
G5	22,466		2088, 8130	2.85	2.81	0.15	0.19	<0.05	1.00
G6	24,291		2558, 10332	2.85	2.81	0.15	0.18	<0.05	1.00

h=0 : Accept the null hypothesis (No difference between groups), h=1 : Reject null hypothesis (difference between groups), 1,2: Refer to ILCB and RLAP, respectively.

The relationship between daily traffic volume and TTC is important for safety. As can be seen in Table 3, although the daily volumes from G1 to G6 increase by about 2-fold, the number of replacement events occurring in ILCB and RLAP conditions increases by about 7-fold. A similar but opposite relationship is observed between daily traffic and mean TTC values. While the TTC value for ILCB decreases from 2.88 s in G1 to 2.85 s in G6, it decreases for RLAP from 2.83 to 2.81. The decline in TTC suggests that vehicles are exposed to more critical collisions. Therefore, the increase in daily traffic leads to an increase in the number of collisions and a decrease in the mean TTC values under both conditions. Although daily traffic increase has similar effects in ILCB and RLAP conditions, the higher intersection number and lower TTC values observed in RLAP conditions suggest that daily traffic increase is more critical to safety in RLAP conditions.

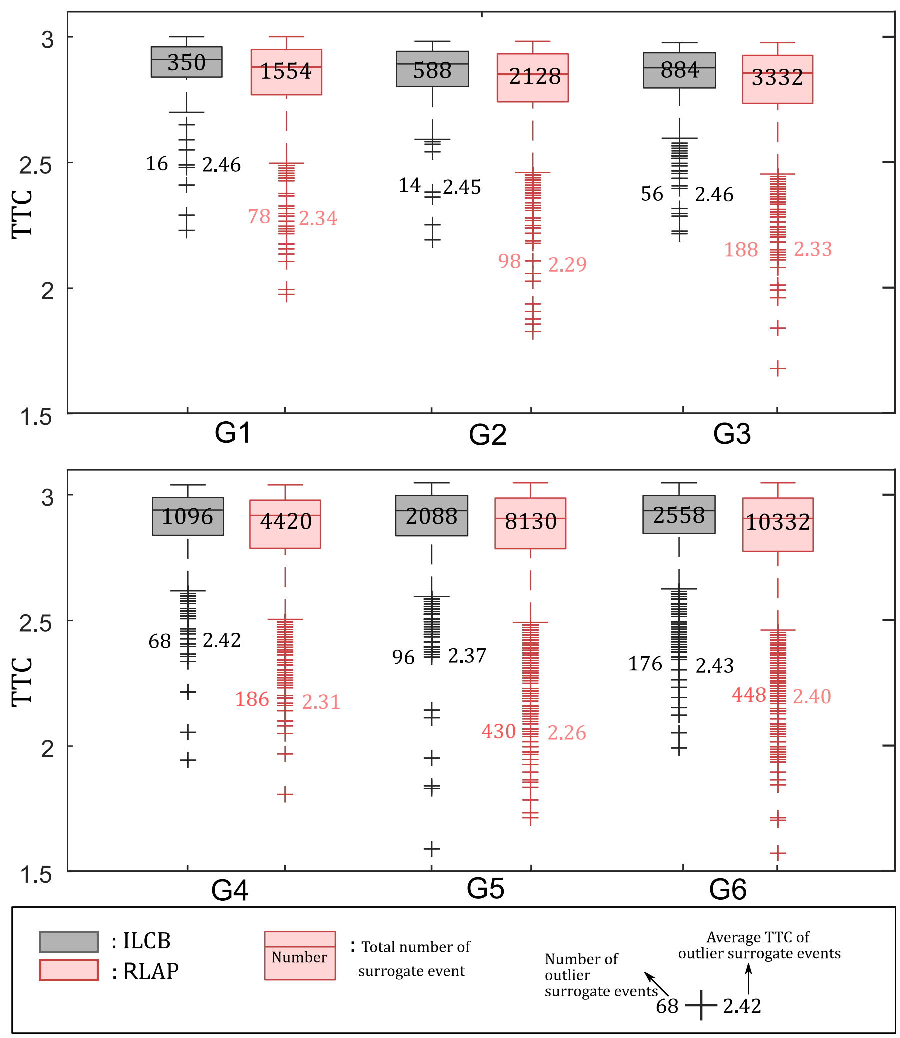

Figure 10. TTC distributions for groups under RLAP and ILCB conditions (The numbers inside the boxes indicate the number of surrogate events.)

Collisions are rare events compared to other interactions in traffic flow. Furthermore, the decrease in TTC values and the increase in substitute event numbers increase the risk of a collision. It turns out that values that fall below the minimum accepted values in the distribution, i.e. outliers, are actually the events that represent the highest risk. For these reasons, it is understood that outliers within the TTC distribution must be analyzed separately. Boxplots for outlier numbers, their minimum achieved values and mean values, as well as the distributions of the TTCs are shown in Figure 10 for traffic groups.

When looking at outliers by group, the first thing that is noticeable is that the number of outliers that occur under ILCB conditions is significantly lower than under RLAP conditions. For example, while 16 outliers are observed for G1 in ILCB, 78 outliers are observed in RLAP. In other words, the risk event is approximately five times more likely to occur under RLAP conditions. When this ratio is calculated considering all groups, we find that RLAP contains, on average, 3.35 times more outliers. Furthermore, a correlation between daily traffic and the number of outlier replacement events is observed under both conditions, suggesting that an increase in daily traffic increases the number of outlier replacement events. Another significant difference for outliers between the two conditions is the mean TTC values (Figure 10, mean TTC values of the outliers). When differences in these values are examined for groups, the mean TTC values of outliers are considered to be between 5% and 7% lower under RLAP conditions than under ILCB conditions. In other words: RLAP significantly leads to the occurrence of higher risks compared to ILCB.

4. Discussion and Conclusion

This study defined the Right Lane Avoidance (RLAP) phenomenon, which is observed when drivers avoid the rightmost lane even under suitable conditions for driving on multi-lane highways in Turkey, and its impact on traffic safety and - performance examined. While previous studies on lane usage have been conducted in Turkey, this study is the first to identify this phenomenon observed in Turkey and examine its impact on lane usage in terms of performance and safety.

To clearly demonstrate the effect of RLAP, ILCB and RLAP conditions were created using real speed and traffic volume data in the SUMO simulation environment, and the results were compared. Road performance analysis shows that as daily traffic increases, the number of vehicles avoiding the rightmost lane also increases, resulting in higher congestion in the middle and leftmost lanes.

Despite the high average speed expectations of FPC-type vehicles, their inability to maintain this speed in the left lanes due to RLAP leads to significantly higher time loss values for this vehicle type compared to ILCB. On the other hand, SPC and MPC-type vehicles, which have the greatest influence on the emergence of RLAP, are less affected than FPCs because, in addition to their lower speed expectations, they avoid the right lane and use only the middle and, when necessary, the leftmost lane. Although this may seem advantageous for these vehicle types, the analysis results indicate that it significantly increases overall delay values.

Buses also emerge as another vehicle type significantly affected by RLAP in terms of time loss. Although the values observed are not as high as those for FPCs, their high passenger-carrying capacity makes the increase in per capita delay a notable disadvantage. Moreover, the standard deviation of the time loss values for buses under RLAP conditions is higher than for other vehicle types, which can be interpreted as some buses slowing down due to intense interaction with other vehicles. This situation may also negatively impact passenger comfort.

From a safety perspective, analysis using surrogate safety measures indicates that more conflicts occur under RLAP conditions compared to ILCB. In other words, RLAP significantly compromises road safety. As expected, analysis based on daily traffic volumes reveals that as volume increases, the number of conflicts under RLAP conditions becomes considerably higher than under ILCB. This is mainly due to increased congestion in the remaining lanes as a result of drivers avoiding the rightmost lane.

Furthermore, the increased congestion in the left lane—where faster vehicles tend to travel—due to RLAP not only leads to a higher number of conflicts but also causes a significant decrease in Time to Collision (TTC) values. In other words, RLAP creates much riskier driving conditions. In such scenarios, the likelihood of sudden braking events increases, which clearly has a negative impact on both road performance and traffic safety.

This study also has some typical limitations found in almost all scientific studies. First, the analyses are based on simulation model results. While simulations offer significant advantages in modeling and comparing different traffic conditions and driver behaviors, some differences from real conditions are inevitable despite calibration processes. In this study, the calibration processes were carried out based on traffic volume. In future studies, performing calibration based on other variables such as speed and investigating how this affects the results could provide valuable insights. Another limitation is the analysis of a limited road segment length for practical purposes. In future studies, it would be appropriate to analyze more road sections and increase the length of the analyzed road to better understand the phenomenon.

In summary, this study clearly shows and discusses how RLAP, which is commonly observed on multilane roads in Turkey, negatively impacts road performance and safety through modeling, testing and analysis. It is expected that the knowledge gained will contribute to the planning of traffic management systems and the implementation of necessary measures in developing countries such as Turkey, where similar phenomena can be observed.

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Author contributions The paper is sole authored.
Declarations
Competing interests The author declares no competing interests

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