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Modeling Driver Stop/Go Decisions in the Dilemma Zone During Amber Signal Phase Under Mixed Traffic Conditions

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Abstract

Traffic safety and operational efficiency at signalized intersections are mainly influenced by drivers' decision during the onset of the amber phase. The region in which drivers are uncertain whether to stop or proceed is known as the dilemma zone which poses significant risks of rear end and right-angle collisions. This study investigates factors affecting drivers' stop/go decisions during the amber interval and develops a decision model for mixed traffic conditions. Two high-crash signalized intersections, Sallaghari and Naya Thimi on the Kathmandu–Bhaktapur Road, were selected based on 2024 crash records. A binary logit model was estimated using variables extracted from videographic surveys and field observations. Video data were processed frame-by-frame at 30 fps using Python libraries such as OpenCV and YOLOv11. A total number of 6462 observations were recorded from both the intersections. Model results showed that approach speed, vehicle type (bus), distance to stop line, intersection type, and acceleration/deceleration were statistically significant in explaining the choice of a "Go" over a "Stop" decision. Overall, 57.97% of the drivers stopped before the stop line, 20.44% crossed during the amber signal phase and 21.59% were spotted in RLR. Buses were more likely to choose the "Go" decision, reflecting aggressive driving and competition for passengers. Accelerating drivers tended to proceed, while decelerating drivers were more likely to stop. The outcomes of this study can support the design of advance warning and enforcement strategies to alert drivers in advance and reduce crashes at signalized intersections.

Keywords: Amber Signal; Mixed Traffic Conditions; Signalized Intersection; Stop/go Decisions

1. Introduction

Traffic signals are mainly placed at intersections to manage the movement of vehicles and pedestrians smoothly. In urban road networks, traffic signalized intersections are essential components where driver's decision has a significant impact on both efficiency and safety. Good signal timing is helpful to operate the flow of traffic safely and efficiently without any conflict and minimizes the chance of crashes. Regulation of traffic is carried out by using red, amber, and green light signals, along with directional arrows of green, amber, and red light and warning signs when required (DoR, 1997). Kathmandu Valley Traffic Police Office (KVTPO, 2025) indicated that the incidences of road crashes in the valley have lowered since past few years due to an increasing trend of installing traffic lights and enforcement related to the use of traffic lights.

An amber light signal is a yellowish orange colour light, where it signals that a driver has to decelerate and be ready to stop since this will turn into a red signal soon. The amber colour is used due to the great visibility of its light to pass on a cautionary sign to drivers (Howell et al., 2015). The amber light gives the same prohibition as the red signal except when the vehicles are stationed in such proximity to the stop line that safely stopping isn't possible and are expected to proceed, and the amber phase generally lasts for three seconds (DoR, 1997). The amber signal phase is one of the most important variables of all signals in traffic lights, operationally and for safety reasons, since the number of traffic crashes at amber phase is the highest in signalized intersections (Yang et al., 2014). The amber interval acts as the phase of transition from the green signal to the red signal; this usually presents a dilemma zone where drivers must decide whether to stop abruptly or go ahead at the intersection. This zone poses a significant safety concern, as vehicles caught here are at a heightened risk of rear-end collisions, red-light violations and intersection crashes reducing the intersection performance.

Researchers have discovered that there are two kinds of dilemma zones: type I and type II (Wei, et al., 2011; Zhang, et al., 2014). First type (type I) was first introduced by Gazis, et al., (1960) which describes the situation of drivers during amber time where they can neither stop safely nor pass clearly before the arrival of stop line. This problem was able to be solved by adjusting minimum amber time. The second type of dilemma zone (Type II) was

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initially identified by the Institute of Transportation Engineers (ITE) and subsequently documented in a technical committee report (Parsonson et al., 1974). This zone is associated with driver's decision taking behavior at the onset of the amber light.

Under mixed traffic conditions, which are common in many developing nations, driver decision-making at signalized intersections is particularly difficult as each vehicle type has its own fundamental characteristics that are driven by the drivers with different driving patterns. In context of Nepal, it can be observed that two-wheelers, three-wheelers, four-wheelers and multi-axle vehicles share the same roadway space. As a result, overtaking among the vehicle type leads to significant variation in speed, maintaining poor lane discipline and increased risk-taking behavior to cross the intersection. The variability in driver behavior, vehicle dynamics, roadway geometry, and signal timing remain a persistent challenge, as poor stop/go decisions lead to right-angle collisions and rear-end crashes at the intersections. Finding the right decision to stop/go at the onset of the signalized intersection helps drivers to cross safely and maintain overall safety of the intersection. Since several studies have been performed to understand the driver's stop/go decision in homogeneous traffic, there is still lack of research in developing nations with heterogeneous traffic condition. So, a deeper understanding of how traffic, vehicle, and driver's approach interact to influence stop/go decisions during the amber signal phase is necessary. This study focuses on identifying and modeling driver stop/go behavior during the amber phase at signalized intersections operating under mixed traffic conditions. The results can potentially benefit traffic engineers, researchers and urban planners in optimizing signal timing and intersection design to improve safety and efficiency.

2. Literature Review

Tang et al. (2015) developed a driver decision model using binary logistic regression to study how yellow and green lights affect driver behavior in dilemma zones. Their research focused on high-speed rural roads in Shanghai, China, with a posted speed limit of 80 km/h. The study focused on intersections that included a sequence of signal phases such as steady green, a brief flashing green lasting three seconds, followed by a yellow phase of the same duration, two seconds for all-interval red for bigger intersections, and one second for medium and smaller intersections. The study found that while several factors influence driver decisions, the most important ones were the distance to the stop line and the type of vehicle.

Li et al. (2016) developed a step-by-step model based on binary logistic regression to examine what factors influence drivers' behaviors in the yellow light, particularly in the dilemma zone. The results revealed that the type of vehicle, speed of the vehicle, and its distance from the stop line were significant factors that influenced drivers to stop or not in the dilemma zone. The two significant factors that influenced drivers to run during a red light were the distance from the stop line and the increase in speed. In general, the model performed well showcasing the results strong in terms of their ability to explain drivers' choices and the level of accuracy and reliability was high.

Pathivada and Perumal (2017) conducted an experiment to observe the behavior of the drivers, after seeing yellow light come up at two major intersections under mixed traffic, in Mumbai-India. To overcome the problems caused by congestion, data collection was done in non-peak hours. Cameras were placed in high location which helped Pathivada and Perumal to observe the traffic behavior of the vehicles coming from both directions they were able to observe the traffic behavior of the vehicles 100-150m from the junction. Their results suggested that of all vehicles which stopped, only 35.5% chose the yellow phase to stop. This represents the aggressive behavior of the drivers. To further investigate the behavior of the drivers the author did further analysis by developing a model using binary logistic regression analysis whose accuracy was found to be 83.3% accurate in predicting what decision the driver makes. The author's analysis revealed that the variables that affect the decision of the drivers were vehicle speed and type, distance from the stop line and the duration of the yellow signal.

Biswas and Ghosh (2018) conducted a comparison of different ways to model how drivers make decisions when facing a yellow traffic light. They used methods like logistic regression, Artificial Neural Network (ANN), fuzzy logic, and the Weighted Average Hybrid Model (WAHM). The data was collected from video recordings taken from 10:00 AM to 2:00 PM on a clear climate, covering a 100-meter road section starting from the stop line. The study found that distance to the stop line, approach speed, and acceleration/deceleration rate affect the drivers' stop-or-go decision for both motorized two-wheelers and cars.

Hussein, (2020) studied the behavior of drivers at yellow light phase at two intersections with traffic signals in Duhok city, Iraq. The study was based on video recordings at two particular locations that were Zari Land and Baroshke. The cameras were placed on a tall building that can record a video footage at least 100 meters from the stop line. The data was analyzed mathematically using the statistical approach of binary logistic regression. A driver's speed and the proximity to the stop line at the instant the yellow light came on were significant factors that influenced the decision to stop or go at the instant the yellow light. The type of the vehicle did not affect the decision of stopping or going was probably due to the types of vehicles in the sample.

Bąk et al. (2021) analyzed drivers' decision of stopping or going just after the onset of the yellow signal in Poland from video observations. Cameras were mounted to record traffic between 20 and 160 meters upstream of the stop line. Data were examined using the binary logarithm regression model. The analysis was performed on the continuous and discrete predictor variables. It was also found that the distance to the stop line, speed of the vehicle, vehicle class, and type of intersection are explanatory variables.

Abhijith & Krishnamurthy, (2022) studied the behavior of drivers in the mixed traffic following the dilemma behavior in three signalized of Thrissur district in Kerala, India. Videographic data collection was done for three hours in each intersection of the road which is 100m far from the stop line. A binary logit model developed for all types of vehicles aggregated as combined vehicle model to investigate the influence of mixed traffic conditions on dilemma drivers due to the presence of amber light signal. The study results indicated that the significant variables which affect the decision making of drivers were distance to stop line, approach speed and amber time. Also, the study contributed to the improvement of safety and signalized intersection performance in developing countries.

Alomari, et al., (2023) investigated the drivers' behavior at eight urban intersections by logistic regression method. The following factors were found significantly responsible during yellow phase for driver stop/go behavior such as approaching speed of vehicle, acceleration and deceleration of the vehicle, the distance of vehicle to the stop line, type of the intersection and yellow light duration. The findings indicated that 60% of drivers proceeded through the intersection during the yellow phase, while 33% managed to stop before the stop line. In contrast, 7% entered the intersection after the signal had turned red, constituting a red-light violation. The analysis results indicated that the binary logistic regression models predicted a higher probability of passing as vehicle speed increased. However, the probability of passing decreased when the distance between the vehicle and stop line along with green interval increased. In addition, the analysis showed that the vehicle type of movement and position of vehicle significantly affect passing behavior while the vehicle type did not show a significant effect.

A comparison of prior models reveals notable differences in methodology, traffic conditions, and model performance across research contexts. Tang et al. (2015) and Li et al. (2016) developed binary logistic regression models under homogeneous traffic conditions in China, reporting model accuracies of approximately 80%, with distance to stop line and vehicle speed as the most dominant predictors. Moreover, Pathivada and Perumal (2017) developed a similar model under mixed traffic conditions in India, achieving an accuracy of 83.3%, with vehicle speed, vehicle type, and distance to stop line as significant variables. Biswas and Ghosh (2018) compared logistic regression against ANN, fuzzy logic, and hybrid models, finding that no single method consistently outperformed others across all vehicle types. Findings show no dominant method across vehicle types. However, the significant findings from Bąk et al. (2021) suggest that type of vehicle and intersection type were additionally significant under high-speed conditions in Poland, whereas Hussein (2020) indicated that vehicle type appears insignificant in Duhok city, Iraq. Also, Abhijith and Krishnamurthy (2022) indicated that a combined vehicle model under mixed traffic in India identified distance to stop line, approach speed, and amber time as significant variables. Notwithstanding these results, Alomari et al. (2023) suggested that acceleration/deceleration and intersection type appear as significant predictors at urban intersections. Most of these studies were conducted under homogeneous traffic conditions with limited vehicle type diversity. None of these studies were carried out in the context of Nepalese mixed traffic conditions where huge percentage of motorized two-wheelers dominate the traffic composition. The present study addresses this gap by developing a binary logit model incorporating vehicle type, approach speed, distance to stop line, intersection type, approach lane, posted speed limit and acceleration/deceleration under the mixed traffic conditions of Nepal.

Previous studies have shown that a driver's decision to stop/go at the onset of an amber signal is largely influenced by factors such as approach speed, vehicle type, and type of intersection. The inclusion of acceleration/deceleration as an independent variable of stop/go decisions is supported by several prior studies. Biswas and Ghosh (2018) identified acceleration/deceleration rate as a significant factor influencing the stop-or-go decision for both motorized two-wheelers and cars at the onset of the yellow phase. Similarly, Alomari et al. (2023) included acceleration and deceleration of the vehicle as a significant predictor of driver stop/go behavior during the amber phase at urban signalized intersections. Papaioannou et al. (2021) further confirmed that acceleration at the onset of the amber indication significantly increases the odds of a driver choosing to "Go" rather than "Stop". In this study, red-light running (RLR) behavior, approach lane, and compliance with the posted speed limit (50 km/h) were examined, as a considerable number of vehicles violate traffic regulations by crossing during the red phase, disregarding lane order, and exceeding the prescribed speed limit operating in heterogeneous traffic. It has been noted in earlier works that driver behavior tends to vary with traffic flow and roadway characteristics at each intersection. Considering these aspects, the present study was carried out at both three-legged and four-legged intersections to capture the variations in driver behavior under the mixed traffic conditions of Nepal.

The present study established acceleration/deceleration as a predetermined kinematic condition rather than a result of the driver's stop/go decision by measuring each vehicle's acceleration/deceleration state over the upstream zone of 100 m from the stop line. As a result, every independent variable considered in this study reflects situation that are prior to the stop/go decision, indicating their function as determinants rather than effects of driver conduct at the beginning of the amber phase.

3. Study Area and Data Collection

3.1 Study Area

The study focuses on modeling dilemma driver stop/go decision making behavior at signalized intersections during an amber phase. Two signalized intersections, Sallaghari and Naya Thimi signalized intersections were selected along Kathmandu-Bhaktapur Road section for the study. Sallaghari is a 3-legged intersection whereas Naya Thimi is a 4-legged intersection. These intersections have been recognized as high crash zone (Aryal & Dhakal, 2024). The crashes involved during afternoon hours from 12:00 PM to 03:59 PM were found to be the highest in Kathmandu-Bhaktapur Road section (Ojha, 2021). Therefore, these intersections were selected for the study during off-peak hours.

Table 1: General Characteristics of Selected Intersections

Intersections	Intersections 1	Intersections 2
Intersection Name	Sallaghari	Naya Thimi
Type of Intersection	3-legged	4-legged
Cycle Time	118 sec	180 sec
Amber Time	3 sec	4 sec
Red Time	55 sec	110 sec
Green Time	60 sec	66 sec
No. of Lanes in Subject Approach	3	3
No. of Selected Lanes in Subject Approach	2	2
Subject Approach	Suryabinayak to Sallaghari Radhe Radhe to Sallaghari	Chardobato to Thimi Radhe Radhe to Thimi
No. of recorded observations	2423	4039

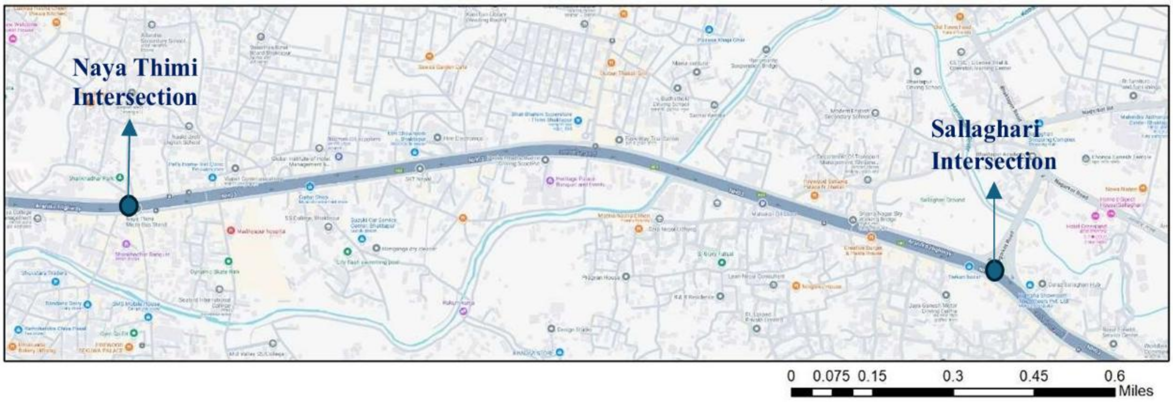

Figure 1: Study Area

Source: Google Maps, 2025

3.2 Traffic Composition

The study was conducted under heterogenous traffic condition consisting of varied composition of motorized vehicles observed at Sallaghari and Naya Thimi signalized intersections during the amber phase. The observations included motorized vehicle types such as cars, trucks, buses, and motorcycles captured across the intersections. All these types of vehicles were grouped into four different categories which are listed in Table 2.

Table 2: Vehicle Type and Vehicle Category

Vehicle Type	Vehicle Category
Motorized two wheelers	Bike, Scooter, Moped
4-Wheelers	Car, Van, Jeep, Pickup, HiAce
Bus	Bus, Minibus
Truck	Truck, Minitruck, Multi-axle truck

3.3 Sample Size

Previous studies conducted in analyzing the dilemma driver behavior at the onset of amber light found that the samples obtained using videographic survey were all taken into action (Pawar et al., 2022; Pathivada & Vedagiri, 2022). This showed that the sample size depends upon the total time of survey performed and traffic volume at the intersection. So, for this study, all the recorded data during off-peak hours by videographic survey were considered as the sample size.

3.4 Data Collection

3.4.1 Primary Data Collection

To collect the primary data, videographic surveys were done at Sallaghari and Naya Thimi signalized intersections of Kathmandu-Bhaktapur Road. The data was collected during off-peak hours to avoid the problem of queuing due to congestion during peak hours. High-definition cameras at specific locations were placed to capture the traffic movements and the driver's response to the amber light. Cameras were placed at the intersection in such a way that it could cover a stretch of 150m from the stop line. Figure 1 illustrates the field setup where small flags at an interval of 10 m were also placed from the stop line which worked as reference points. The approach speed was measured by frame-by-frame analysis at 30 FPS to pass the trap length of 50 m and was recorded 100m ahead of the intersection.

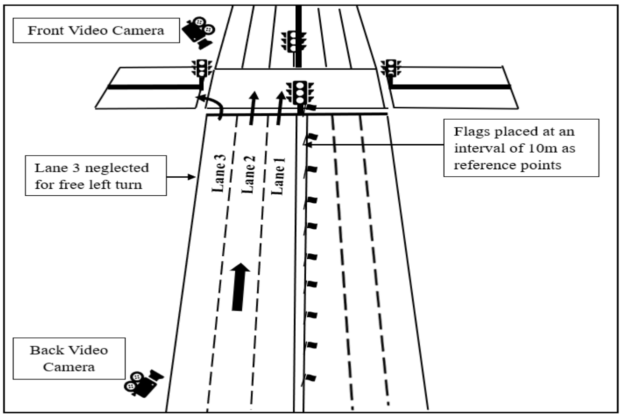

Figure 2: Illustration of field setup

3.4.2 Secondary Data Collection

For the crashes that occurred across Kathmandu-Bhaktapur Road section, last three years data were collected from Kathmandu Valley Traffic Police Office (KVTPO, 2025) which showed that crashes near Naya Thimi and Sallaghari intersection were high. Kandel, et al., (2023) observed that peak hours in Kathmandu-Bhaktapur route were between 9:00 AM to 11:00 AM and 4:00 PM to 6:00 PM. Based on this information, the off-peak hour for this study has been set between 12:00 PM to 4:00 PM for two weekdays as the number of crashes involved were observed to be highest during this period (Ojha, 2021).

4. Methodology

4.1. Data Analysis

The video footage was analyzed frame by frame at 30 FPS using YOLO 11 (You Only Look Once Version 11) and Open CV (Open-Source Computer Vision) libraries to observe drivers' response. YOLO is an approach that treats object detection as regression problem which frames them as separate dimensional bounding boxes and associated class probabilities on a real time basis. It utilizes a single Convolutional Neural Network (CNN) and predicts multiple bounding boxes along with every probable class simultaneously. Moreover, YOLO is known for its speed and accuracy, has the ability to process images at 45 frames per second (FPS) and achieve high mean Average Precision (mAP) compared to other real-time systems (Redmon et al., 2016). Acceleration and deceleration of each vehicle were measured by differentiating the speed at 100 m and stop line whereas the vehicles speed were monitored at 100m which showed that the approaching vehicles are under posted speed limit of 50 km/hr.

Figure 3: Video output after using YOLO and Open CV libraries

A binary logit model (BLM) was applied to analyze and develop dilemma driver stop/go decision at signalized intersections. A binary logit model predicts the probability of a dichotomous outcome which is a form of logistic regression.

The binary logistic regression can be represented as the following formula:

$$logit(p) = ln\left(\frac{p}{1-p}\right) = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots + \beta_n X_n \quad (1)$$

Where,

p	:	probability of driver deciding to go during amber phase at the intersection
β_o	:	intercept
β_n	:	coefficient of each variable
$X_1, X_2, \ldots\ldots, X_n$	:	variables

4.2. Variables description

The data extracted from video analysis contained both continuous and categorical variables as shown in Table 2. The categorical variables were dummy encoded with one category from each variable treated as the reference group against which the remaining categories were compared. Furthermore, these variables included driver decision (stop or go), vehicle type (motorized two-wheeler, motorized four-wheeler, bus, truck), intersection type (3-legged or 4-legged), lane type (Lane 1 or Lane 2), posted speed-limit compliance (≤50 km/h: yes or no), acceleration state (deceleration or acceleration), and red-light running status (yes or no). Approach speed (km/h) and distance to stop line (m) were modeled as continuous variables.

Table 3: Variables description

Variable	Type	Encoded	Description
Decision	Categorical	0: Stop 1: Go	Driver decision during amber signal
Approach Speed	Continuous	Km/hr	Speed of the vehicle while approaching the intersection
Distance to Stop line	Continuous	Meter	Position of the vehicle from the stop line at the start of amber signal
Intersection Type	Categorical	0: 4-legged 1: 3-legged	Intersection legs
Vehicle Type	Categorical	0: M2W 1: 4W 2: Bus 3: Truck	Various motorized vehicles
Lane Type	Categorical	0: Lane 2 1: Lane 1	Lane 1 is rightmost lane (near median) while lane 2 is the lane to its left
Acceleration/ Deceleration	Categorical	0: Decelerate 1: Accelerate	Rate of change of speed
Posted Speed Limit (50 km/hr)	Categorical	0: No 1: Yes	Maximum speed shown on traffic signpost

The driver's binary stop/go decision at the start of the amber signal is the dependent variable in this study. Every independent variable was chosen based on proof that it was a determinant found in the body of existing literature. Approach speed, distance to stop line and type of intersection represent physical conditions of amber onset that constrain the feasible options available to the driver. Acceleration/deceleration precedes the decision in time by capturing the vehicle's kinematic motion just prior to the amber onset. This characteristic has been shown in studies to be a predictor of driver decisions. The posted speed limit is a pre-existing regulation that is structurally unaffected by the choices made by drivers. These factors serve as independent predictors because they are all measured or fixed before the stop/go decision.

4.3. Descriptive Statistics of the variables

The descriptive statistics of variables with mean, standard deviation (SD), minimum and maximum values along with their percentage distribution including sub-level categories are presented in Table 4. The vehicle count data is shown from all the observation done during the weekdays of videographic survey. From 6462 total observations, 42.03% were found to be passing through the amber light signal while approximately 57.97% denied crossing the intersection and stopped. Additionally, Motorized two-wheelers (M2W) with 61.84% occupied the maximum proportion of vehicles on road followed by four-wheelers (4W) with 21.40% along with bus and truck with 9.36% and 7.40% respectively. Furthermore, 46.69% of vehicles accelerated and 53.31% of vehicles decelerated while approaching the intersection. Also, 48.65% of vehicles approached through lane 1 whereas 51.35% of vehicles approached through lane 2. About 75.35% of the vehicles were found to be running under posted speed limit of 50 km/hr and rest 24.65% passed above it.

It was also observed that 20.44% of drivers passed during the amber signal phase, 21.59% drivers were spotted in RLR and rest stopped before the stop line. Here, 21.59% of RLR rate observed in this study is substantially higher than the 7% reported by Alomari et al. (2023) in urban signalized intersections, suggesting that the Kathmandu-Bhaktapur Road section experiences a considerably higher prevalence of aggressive driving behavior. This aggressive nature of drivers attempting to cross during the amber phase were found more likely to end up running the red signal. Also, RLR rate at 4-legged is more than double that at 3-legged intersections, with 35.05% of vehicles exhibiting RLR behavior at 4-legged intersections compared to 16.31% at 3-legged intersections. Longer signal cycle timings and increased perceived waiting periods may be linked to the higher RLR rate at 4-legged crossroads which may encourage some drivers to take on more risk and drive through the red signal phase.

Table 4: Descriptive statistics of variables

Variables	Mean	SD	Min	Max	Sub-level		Vehicle Count	Percentage (%)
Approach Speed	40.95	11.98	15.0	70				
Distance to Stop line	53.84	30.33	5.0	115				
Type of Intersection					3-legged		2423	37.50
					4-legged		4039	62.50
Red Light Running (RLR)					Yes	3-legged	443	16.31
						4-legged	952	35.05
					No		1321	48.64
Decision					Stop		3746	57.97
					Go		2716	42.03
Vehicle Type					M2W		3996	61.84
					4W		1383	21.40
					Bus		605	9.36
					Truck		478	7.40
Acceleration/ Deceleration					Accelerate		3017	46.69
					Decelerate		3445	53.31
Approach Lane					Lane 1		3057	47.31
					Lane 2		3405	52.69
Posted Speed Limit (PSL)					Yes		4869	75.35
					No		1593	24.65

5. Result and Discussion

5.1. Binary Logit Model

First, multicollinearity test was performed so that there exists no significant multicollinearity between the independent variables. Approach speed was used as the dependent variable in the linear regression since VIF and tolerance are derived from the interrelationships among predictor variables. Table 5 shows VIF values for all variables between 1.006 and 1.087, while the corresponding tolerance values varied between 0.920 and 0.994. All VIF values were below the standard threshold of 3.3 (Kock, 2015). And tolerance values ranged from 0.920 to 0.994 which are above the minimum threshold of 0.1 (Hair et al., 2010). This shows no evidence of problematic multicollinearity among the independent variables.

Table 5: Multicollinearity diagnostics: Tolerance and VIF for predictor variables

Variables	Tolerance	VIF
Vehicle_Truck	0.943	1.061
Vehicle_Bus	0.944	1.060
Vehicle_4w	0.931	1.074
Distance to Stop line	0.920	1.087

Intersection Type	0.965	1.037
Acceleration/Deceleration	0.922	1.085
Approach Lane	0.994	1.006
Posted Speed Limit	0.972	1.029

Dependent Variable: Approach Speed

A binary logistic regression model was developed with the combination of significant continuous and categorical variables influencing driver to stop/go at the onset of amber light. From a total of 6462 total observations, eighty percent, i.e. 5172 observations were considered for model development and remaining twenty percent i.e. 1290 observations were considered for model validation.

Table 6 shows the Omnibus Test of Model Coefficients that the model with predictors was statistically significant, $\chi^2_{10} = 2619.462$, p < 0.001, indicating that inclusion of the predictors significantly improved model fit compared with the intercept only model.

Table 6: Omnibus Test of Model coefficient

Model	Chi-square	df	Sig.
	2619.462	9	0.000

Table 7 presents additional measures of model fit. The −2 Log Likelihood value of 3149.287, together with the pseudo-R^2 statistics, suggests that the model provides an adequate representation of the observed data. The Cox & Snell R^2 of 0.491 and Nagelkerke R^2 of 0.602 indicate that the model explains a substantial proportion of the variability in drivers' decisions to proceed through the intersection. These relatively high pseudo-R^2 values suggest that the selected predictors (vehicle type, intersection type, posted speed limit, red light running, and acceleration/deceleration) are effective in modeling driver decision making behavior.

Table 7: Model fit statistics

Model	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
	3149.287[a]	0.491	0.602

Table 8 presents the regression coefficients and associated statistics for the predictors included in the model estimating the probability of a 'Go' decision relative to a 'Stop' decision at signalized intersections. The 95% confidence intervals (CI) for the odds ratios Exp(B) where a CI that does not include the value 1.0 shows statistical significance of the predictor at the 5% level. Positive coefficients indicate that higher values of a predictor increase the likelihood of a 'Go' decision, whereas negative coefficients indicate a decrease in this likelihood.

Table 8: Parameter estimates for 'Go' decision model with 95% confidence intervals

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP (B)	
							Lower	Upper
Vehicle Type			9.381	3	0.025			
Vehicle Type (Truck)	0.188	0.132	2.022	1	0.155	1.207	0.931	1.564
Vehicle Type (Bus)	0.327	0.118	7.732	1	0.005	1.387	1.101	1.747
Vehicle Type (4W)	0.128	0.090	2.022	1	0.155	1.136	0.953	1.355
Approach Speed	0.050	0.004	124.290	1	0.000	1.051	1.042	1.060
Distance to Stop line	-0.047	0.001	976.171	1	0.000	0.954	0.952	0.957
Intersection Type (3-legged)	-0.185	0.073	6.427	1	0.011	0.831	0.974	1.298
Acceleration/ Deceleration (Accelerate)	0.901	0.070	165.480	1	0.000	2.461	2.146	2.823

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0

Approach Lane (Lane 1)	0.075	0.070	1.153	1	0.283	1.078	0.940	1.236
Posted Speed Limit (Yes)	0.014	0.120	0.014	1	0.907	1.014	0.802	1.283
Constant	-0.657	0.175	14.166	1	0.000	0.518		

Based on the results obtained in Table 8, estimated logit model for 'Go' decision can be written as

$$Logit(P) = -0.657 + (0.327 * Vehicle\ Type\ (Bus)) + (0.050 * Approach\ Speed) - 0.047 * Distance\ to\ Stop\ line) - 0.185 * Intersection\ Type\ (3 - legged)) + (0.901 * Acceleration/Deceleration\ (Accelerate)) \quad (2)$$

5.1.1 Parameter Description from Binary Logit Model Results

In vehicle type, motorized two-wheeler was assumed as base vehicle as it occupied more than 60% of total fleet with maximum variations towards their decision when approaching the amber signal. The vehicle type variable as a whole is statistically significant (Wald = 9.381, df = 3, p = 0.025) confirming that vehicle type collectively influences the Go/Stop decision. Buses showed a greater likelihood of deciding for the "Go" decision during amber signal in comparison to 4-wheelers and truck. It is the only vehicle subtype that is individually statistically significant (Exp(B) = 1.387, CI [1.101, 1.747], p = 0.005). While trucks and 4-wheelers also show higher odds of a "Go" decision compared to motorized two-wheelers, these differences are not statistically significant at the 5% level.

The positive coefficient for approach speed signifies that, as speed increases, the odds of choosing a "Go" decision increase by 5.1% rather than a "Stop" decision (Exp(B) = 1.051, 95% CI [1.042, 1.060]) which means drivers travelling with higher speeds are more likely to proceed through the intersection than to stop. Approach speed recorded a Wald statistic of 124.290, identifying it as one of the strongest and most reliable predictors in the model. Among all predictors, distance to stop line emerges as the single most statistically dominant variable with the highest Wald value of 976.171 in the entire model and very small standard errors reflecting high precision and strong confidence in these predictors. Odds of a driver making a 'go' decision over a 'stop' decision decreases by 4.6% for every one unit increase in distance from the stop line (Exp(B) = 0.954, 95% CI [0.952, 0.957]). Drivers nearer to the intersection are more willing to make a "Go" decision than a "Stop" decision, while those away from the stop line are prone to stop. Similar research performed under mixed traffic in India showed that stopping probability of the vehicle decreased with an increase in their approach speed and increased with an increase in distance to the stop line (Pathivada & Perumal, 2017).

Drivers approaching a 3-legged intersection are about 16.9% less likely to choose "Go" than those at 4 legged (Exp(B) = 0.831, 95% CI [0.974, 1.298]), based on the intersection type's negative coefficient. The drivers' decision to "Stop" at 3-legged intersection may be related with lower cycle time compared to that of 4-legged intersection. The chances that a driver will choose to "Go" instead of "Stop" increases by about 146.1% when they are accelerating (Exp(B) = 2.461, 95% CI [2.146, 2.823]). These results demonstrate that driver acceleration influences the possibility of a "Go" decision. This outcome is consistent with Papaioannou et al. (2021) whose findings showed that the estimated odds ratio in the final model of binary choice model for acceleration/deceleration at the onset of the yellow indication is 5.56, implying that a 1 m/s^2 increase in acceleration is associated with more than a fivefold increase in the odds of a driver choosing to "Go" rather than "Stop".

Approach lane (lane 1 vs reference lane 2) and Posted speed limit have Wald p-values greater than 0.05 (p = 0.283 and p = 0.907, respectively), indicating that their coefficients are not significantly different from zero in the binary logistic model. This means that, after controlling for the other variables in the model, approach lane and posted speed limit do not have a statistically significant effect on drivers' "Stop/Go" decisions at the onset of the amber signal.

5.2. Model Validation and Performance

Validation for the developed model was carried out using the remaining 1290 (20%) data of driver observations. As shown in Table 9, a confusion matrix was developed to show the actual and predicted stop/go decision. Sensitivity and specificity values of 80.89% and 83.51% were obtained, indicating the model's ability to correctly identify stop/go decision. Overall accuracy of 82.01% is strong enough to predict driver decisions at the onset of amber light at signalized intersection.

Table 9: Confusion Matrix

Actual	Predicted		Percentage Correct
	Stop	Go	
Stop	597	141	80.89%
Go	91	461	83.51%
	Overall accuracy		82.01%

For model performance, Receiver Operating Characteristic (ROC) curve was used in Figure 2 which illustrates the model's ability to discriminate between drivers stop/go decision during the amber signal interval. When the cutoff value is selected to 0.3 in the classification, sensitivity and specificity values of model are found to be 90.06% and 79.97% respectively indicating that it is particularly effective at correctly identifying drivers who choose to "Go". The overall predictive accuracy for the model was measured by area under the ROC curve (AUC= 0.928). This value of AUC represents good predictive performance for the prediction of stop/go decisions of the driver.

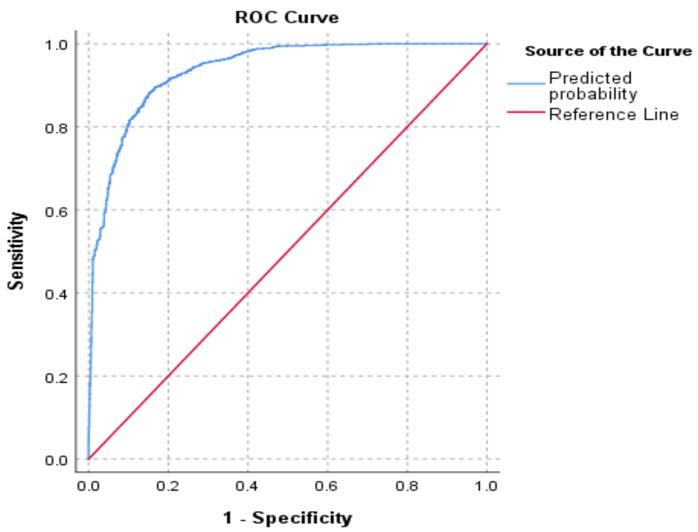

Figure 4: Receiver Operating Characteristic (ROC) curve

6. Conclusion and Recommendation

The driver "Go" over "Stop" decision model was formulated using binary logistic regression for two signalized intersections (Naya Thimi and Sallaghari) with vehicle type, approach speed, distance to stop line, intersection type, approach lane, acceleration/deceleration and posted speed limit as predictor variables. Preliminary tests were performed that concluded that no multicollinearity exists between independent variables as variance inflation factors (VIF) was in between 1.006 and 1.087 which is less than the threshold of 3.3. A binary logit "Go" decision model was developed using only the statistically significant predictors. Approach speed, distance to stop line, intersection type, acceleration/deceleration, and bus in vehicle type were found to be significant variables with p-value less than 0.05 contributing towards the model and all other predictors were proved to be insignificant. Each significant predictors with positive and negative coefficient in the model signifies direct as well as opposite relation with the "Go" decision. Approach speed with positive coefficient shows direct impact towards the decision resulting as speed increases, drivers are more likely to go. Also, the negative coefficient of distance to stop line shows as distance increases drivers are less likely to go and choose to stop. Similarly, the negative coefficient in intersection type signifies that drivers are less likely to cross through 3-legged intersection and decide to stop but try to cross through 4-legged intersection.

Based on the results from this research, following are the recommendations to the transport planners and concerned departments of the valley:

- RLR incidence is high at these intersections, red-light cameras are recommended to maintain the intersection safety and enforce traffic laws.
- Installing countdown timers assists dilemma drivers for making safer stop/go decisions during amber phase.
- It is recommended to install Advance Warning Flashers (AWFs) to alert approaching drivers which lights few seconds before the start of amber light.
- Buses prefer "go" decision over "stop" decision which shows competing nature among themselves to collect more passengers. So, it is recommended to make buses operate only in their provided dedicated lane.

7. Limitations and future possibilities

The limitations of this study are as follows:

- Demographic data of the drivers such as age, gender and education level were not considered.
- The study did not examine the emotional state of drivers.
- The study was conducted on a level road gradient and under clear weather condition

Further future research can be done considering the following points.

- The study can be conducted on roads with varying gradients.
- Drivers' stop/go behavior can be studied under rainy daytime conditions as rain significantly reduces the visibility.
- A questionnaire survey can be included to collect drivers' demographic data.

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