Impact of time pressure on acceleration behavior and crossing decision at the onset of yellow signal

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Abstract: This study investigates acceleration behavior and crossing decision of the drivers under increasing time pressure driving conditions. A typical urban route was designed in a fixed-base driving simulator consisting of four signalized intersections with varying time to stop line (4 s and 6 s) and maneuver type (right-turn and go-through). 97 participants' data were obtained under No Time Pressure (NTP), Low Time Pressure (LTP), and High Time Pressure (HTP) driving conditions. The acceleration behavior was examined at the onset of yellow signal in four ways: continuous deceleration, acceleration-deceleration, deceleration-acceleration, and continuous acceleration. A random forest model was used to build an acceleration behavior prediction model for identifying the significant explanatory variables based on variable importance ranking. Further, a Mixed Effects Multinomial Logit (MEML) model was developed using the explanatory variables obtained from a random forest model. Additionally, a generalized linear mixed model was incorporated for estimating the likelihood of crossing an intersection by considering all the explanatory variables. A MEML model result revealed that the odds of adopting acceleration-deceleration, deceleration-acceleration, and continuous acceleration instead of continuous deceleration increased by 63 %, 123 %, and 77 %, respectively under HTP driving conditions. Moreover, the likelihood of crossing a signalized intersection increased by 2.73 times and 4.26 times when the drivers were under LTP and HTP driving conditions, respectively as compared to NTP driving condition. Apart from this, time to stop line (reference: 6 s) and age showed negative association with crossing probability. Overall, the findings from this study revealed that drivers altered their acceleration behavior for executing risky driving decisions under increasing time pressure driving conditions.

Keywords: Acceleration behavior; Crossing decision; Yellow signal; Time pressure; Random forest; Mixed effects multinomial logit model.

1. Introduction

Intersection is an integral part of roadway system providing access to numerous vehicles intending to converge, diverge, or go through as per their desired destination. Intersection is a common space shared by numerous vehicles at the same time leading to traffic conflicts of varying severity. Drivers need to judge speed and direction of other vehicles to safely cross the intersection area. A minute error in judgement from a driver may lead to road crash (AASHTO, 2011; Mathew, 2009). Due to this reason, traffic signals are installed to minimize hazardous vehicular interactions by providing right-of-way to non-conflicting traffic movements at regular intervals. Installation of traffic signals is found to be an effective solution for reducing traffic crashes occurring at un-signalized intersections (Indo-HCM, 2017; Mathew, 2009). However, safety analysis of signalized intersections revealed that drivers deliberately or accidentally either abruptly stop or cross the intersection during the onset of yellow/red signal leading to traffic conflicts. According to the 2018 annual road crash statistics of the USA, nearly 32 % of the total intersection-related crashes befell at signalized intersections (U.S. Department of Transportation Federal Highway Administration, 2021). In China, 30 % of the total traffic crashes occurred in the vicinity of signalized intersections (Jiang et al., 2021). The study conducted by the State of Queensland, Department of Transport and Main Roads (2018) revealed that 5.3 % of fatalities ensued at signalized intersections. Great Britain recorded 31.89 % KSI (Killed or Seriously Injured) crashes at signalized intersections (Murphy et al., 2020). In 2019, India recorded 7.74 % intersection-related crashes at signalized intersections with 7.14 % fatalities. These statistics indicate that driving behavior at signalized intersection must be assessed in terms of driving attributes, driver demographics, driving condition, and other related factors to investigate the factors persuading drivers' decision and compromising their safety.

Prior research has documented that decision-making during yellow signal is complex and critical than red signal because drivers need to quickly decide whether to stop or cross the intersection (Choudhary and Velaga, 2019; Haque et al., 2016; Mishra and Zhu, 2015). Yellow signal is a warning of a forthcoming change in the right-of-way. It is safe for the drivers to stop before the intersection after the onset of yellow signal. The drivers approaching a signalized intersection may experience dilemma and fail to take a decision, either to stop or cross when the signal changes from green to yellow (Elmitiny et al., 2010; Eluru and Yasmin, 2016). An inappropriate decision at the onset of yellow signal might result in red light running or abrupt braking to stop at the intersection. Here, it is important to note that drivers' decision can be highly influenced by various driving conditions such as distraction, inattention, time pressure, etc. (Bonneson and Zimmerman, 2004; Palat and Delhomme, 2016). It is observed that the crossing probability decreases during distraction and inattention whereas increases in time pressure as compared to normal driving conditions (Choudhary and Velaga, 2019; Fitzpatrick et al., 2017). Time pressure is defined as a driving condition where drivers are under psychological stress to reach their desired destination within constrained time (Dogan et al., 2011; Gelau et al., 2011; Pawar and Velaga, 2020; Rendon-Velez et al., 2016). Due to this reason, drivers adopt high speed driving in order to cover maximum distance in minimum time

(Fitzpatrick et al., 2017; Rendon-Velez et al., 2016). Drivers under time pressure at signalized intersections intentionally take risky driving decisions (red light running) to save time which could have been lost while waiting during yellow and red signals. The odds of taking risky decisions varies as per the extent of time constraint and its perception from the drivers during time pressure driving conditions (Cœugnet et al., 2013; Fitzpatrick et al., 2017). However, drivers traveling at high speed fail to gain rapid acceleration within short distance which might alter their crossing decision at signalized intersection (Palat and Delhomme, 2016). Therefore, the current study is conducted to evaluate acceleration behavior of the drivers and its influence on crossing decisions at the onset of yellow signal under time pressure driving conditions.

The remainder of the paper is organized as follows. The following section broadly discusses various studies conducted on evaluating driving behavior and crossing decision at signalized intersections. Section 3 provides description related to the design of study. Section 4 demonstrates statistical modeling results and its interpretation. Section 5 presents discussion on the results obtained from the current study. Section 6 concludes the paper and section 7 highlights the important contributions of the study. Section 8 describes limitations and future scope of the study.

2. Previous work on driver behavior at signalized intersection

An extensive literature review revealed that abundant research work has been conducted to assess drivers' decision at signalized intersection in real and simulated worlds. The following sub-sections provide an overview of previous research studies considering driving environment (real and simulation), time pressure, acceleration behavior, and crossing decision.

2.1 Previous field and experimental studies on signalized intersection

Over the years, traffic safety researchers showed special interest in analyzing driving behavior and decision making of the drivers at signalized intersections. Majority of the work was conducted in field where the researchers collected video graphic data for modeling drivers' crossing decisions (Kassim et al., 2014; Kim, W., Zhang, J., Fujiwara, A., Jang, T. Y., & Namgung, 2008; Kumar et al., 2019; Pathivada and Vedagiri, 2021; Rakha et al., 2008; Tarko, Andrew, Wei Li, 2006; Yan et al., 2005). Researchers developed binary logit model for estimating stopping or crossing probability at the onset of yellow signal as a function of speed, distance, perception-reaction time, deceleration rates, category of vehicle, and time of day. In the end, dilemma zone boundaries were proposed to counter the influence of uncertainty at the onset of yellow signal (Papaioannou, 2007; Pathivada and Vedagiri, 2021). In the similar direction, driving simulator experiments were conducted for predicting drivers' decision using binary logit model to develop innovative countermeasures for yellow and red light violations (Hussain et al., 2020b, 2020a). Various driving simulator experiments were conducted to investigate drivers' decision at signalized intersection by considering potential implications of human factors (Abdel-Aty et al., 2009; Caird et al., 2007; Hussain et al., 2020b). Majority of driving simulator studies analyzed crossing decision of the drivers in distracted state (distraction due to mobile phone, eating, drinking, etc.) (Choudhary and Velaga, 2020, 2019; Haque et al., 2016, 2012). The authors adopted hybrid approach of decision tree and logistic regression for modeling drivers' crossing decision at signalized intersections (Ali et al., 2021; Choudhary and Velaga, 2019; Haque et al., 2016). Apart from this, Caird et al. (2007) performed a driving simulator study for examining older and younger drivers' driving performance at the onset of yellow signal. The authors observed that older drivers approached intersection at lower speed and most likely stopped at the intersection after the onset of yellow signal. Jahangiri et al. (2016) studied field as well as driving simulator data to predict red light violation at signalized intersections. The authors adopted random forest technique to develop red light violation prediction model. It was reported that driving simulator data resulted in more accurate prediction as compared to field data. This was mainly due to the fact that driving simulator data accounted for driver characteristics (age and gender), scenario configurations, and specific driving conditions (usage of handheld and hands-free mobile phone) (Jahangiri et al., 2016).

2.2 Factors influencing crossing decision at signalized intersections

Extensive research conducted on signalized intersection showed that drivers' crossing decision was mainly influenced by driving speed and distance to stop line at the onset of yellow signal (Papaioannou, 2007; Pathivada and Vedagiri, 2021). It was observed that drivers traveling with speed more than 80 kph and 113 m away from the stop line at the onset of yellow signal were more likely to cross the intersection (Elmitiny et al., 2010). Apart from this, reaction time and mean acceleration had substantial impact on crossing decision of the drivers. The crossing probability was observed to decrease with increment in reaction time after the onset of yellow signal resulting in abrupt deceleration from the drivers (Rakha et al., 2008; Zhang et al., 2014).

Crossing decision was also observed to vary according to driver demographics and scenario configuration. Interestingly, research conducted by Haque et al. (2016) and Abdel-Aty et al. (2009) revealed contrary findings related to crossing decision of male and female drivers. Haque et al. (2016) reported that female drivers were more likely to cross the intersection whereas Abdel-Aty et al. (2009) stated that female drivers were more likely to stop at the intersection. Further, Choudhary and Velaga (2019) studied the influence of age and type of maneuver on crossing decision at the onset of yellow signal. The authors reported that non-distracted mid-age drivers approaching go-through intersection with driving speed of more than 57 kph had high chances of crossing the intersection when the signal turned from green to yellow. Ali et al. (2021) examined crossing decision of the drivers in a connected environment and observed that young drivers with driving speed less than 37 kph, variation in longitudinal acceleration more than 0.43 m/s^2, and driving experience of more than or equal to 8.25 years had lower propensity to cross the intersection at the onset of yellow signal. Caird et al. (2007) discovered that 92 % young-age drivers and 75 % old-age drivers stopped at the intersection when time to stop line was 3.58 seconds. Thus, it can be understood that driving attributes along with driver demographics and scenario configuration significantly influenced drivers' crossing decision at the onset of yellow signal.

2.3 Effects of time pressure on acceleration behavior and crossing decision

Time pressure is one of the foremost contributors to aggressive and risky driving behavior (Cœugnet et al., 2013; Peer, 2010). Numerous studies were conducted in the last decade for evaluating driving behavior under time pressure driving conditions (Gelau et al., 2011; Lee and LaVoie, 2018; Pawar and Velaga, 2021a; Schmidt-daffy, 2013). However, majority of the research work focused on driving behavior at midblock sections and very limited studies examined drivers' decision making at intersections (Gelau et al., 2011; Paschalidis et al., 2018; Rendon-Velez et al., 2016). Fitzpatrick et al. (2017), Palat and Delhomme (2016), and Dogan et al. (2011) analyzed driving behavior of the drivers at signalized intersections. Fitzpatrick et al. (2017) examined drivers' crossing decision when the signal turned from green to yellow under No Time Pressure (NTP), Low Time Pressure (LTP), and High Time Pressure (HTP) driving conditions. NTP was the baseline condition where no time constraint was imposed whereas LTP and HTP driving conditions demanded drivers to complete the driving sessions in constrained time. The authors requested drivers to complete LTP and HTP driving sessions within 85^{th} and 15^{th} percentile travel time recorded during NTP driving session. It was observed that drivers under HTP accelerated faster than LTP and NTP driving conditions. Around 68 % of the total drivers were observed to cross the intersection under HTP driving conditions. No significant increment in crossing decisions was observed in LTP and NTP driving conditions (Fitzpatrick et al., 2017). Palat and Delhomme (2016) studied yellow signal and red signal running tendency of the drivers under NTP and time pressure driving conditions. The risk perception analysis revealed that drivers considered traffic signal violation as a risky decision. However, significant number of drivers were observed to violate traffic signal regulations under time pressure (Palat and Delhomme, 2016). Dogan et al. (2011) analyzed driving behavior of the drivers in the vicinity of signalized intersection under time pressure driving conditions. It was observed that drivers under time pressure approached the intersection at high speed, swiftly reacted and hastily decelerated to stop the vehicle (Dogan et al., 2011). Table 1 provides a summary of the previous research work conducted on signalized intersections considering potential implications of human factors.

Table 1 Summary of previous research work conducted on driving simulator for evaluating crossing decision at the onset of yellow signal

Study	Sample size	Scenario configuration	Statistical modeling	Major findings
Time pressure studies				
Fitzpatrick et al. (2017)	36	YSD: 4 seconds	Unpaired t-test	Drivers under high time pressure were more likely to cross the intersection
Palat and Delhomme (2016)	94	DSL: 59 m; YSD: 4.3 seconds	Chi-square test	Time pressure increased to likelihood of crossing the intersection when the signal turned from green to yellow
Dogan et al. (2011)	36	TSL: 3 seconds; YSD: 2 seconds	Univariate ANCOVA	Drivers under time pressure approached the intersection at high speed, swiftly reacted and adopted abrupt braking to stop the vehicle
Other relevant studies				
Ali et al. (2021)	78	TSL: 5 seconds; YSD: 3 seconds	Decision tree and panel mixed logit model	Drivers in connected environment showed less propensity to cross the intersection at the onset of yellow signal

Hussain et al. (2020b)	67	DSL: 80 m and 95 m; YSD: 4 seconds	Logistic regression	Unit increase in speed (kph) at the onset of yellow signal increased crossing probability by 5.3 %
Choudhary and Velaga (2019)	74	TSL: 3, 4, and 5 seconds; YSD: 3 seconds	Decision tree and generalized linear mixed model	The chances of crossing an intersection were 17% lesser for the music player distraction than phone conversation
Haque et al. (2016)	69	TSL and YSD: 3 and 3.75 seconds;	Decision tree and generalized estimation equations	Young and mid-aged drivers showed low propensity of crossing whilst distracted irrespective of driving speed
Abdel-Aty et al. (2009)	62	DSL: 90 m; YSD: 4.3 seconds	Logistic regression	High variability in crossing decisions were observed at signalized intersection with high risk of rear-end conflict
Caird et al. (2007)	77	YSD: 4.08, 4.58, and 5.08 seconds	Logistic regression	A perception response time of 1 second was deemed sufficient for all age groups to detect change in signal from green to yellow

TSL = Time to Stop Line; YSD = Yellow Signal Duration; DSL = Distance to Stop Line; ANCOVA = Analysis of covariance

2.4 Research objective and hypothesis

Majority of field studies conducted for evaluating crossing decision at signalized intersection were unable to account the effect of human factors and acceleration behavior. This was mainly because of the limitation of data collection technique. Video-graphic data collection is useful for capturing crossing and stopping decisions of vehicle population at a particular signalized intersection (Pathivada and Vedagiri, 2019). Video-graphic data fails to capture individual driver's driving behavior in terms of accelerator pedal and brake pedal applications and driving conditions (use of mobile phone, alcohol-impaired driving, time pressure, etc.). Further, it is very difficult to capture individual driver's driving behavior during yellow phase in field conditions because there is very limited time for encountering yellow signal and the driver has to precisely approach the signalized intersection at the onset of yellow signal. Due to these limitations, the current study was conducted on a driving simulator with a primary goal of investigating the impact of time pressure on acceleration behavior and its influence on drivers' decision (stop/cross) at the onset of yellow signal. Three broad research hypotheses were derived for the current study as shown below:

(i) Time pressure will alter drivers' acceleration behavior and crossing decisions at the onset of yellow signal.
(ii) Variation in time to stop line will affect drivers' acceleration behavior and crossing decisions at the onset of yellow signal.
(iii) Driver demographics will influence drivers' acceleration behavior and crossing decisions at the onset of yellow signal.

3. Materials and Methods

3.1 Design of experiment

An extensive literature review was conducted to identify the problems or limitations from the previous studies. It was observed that acceleration behavior at the onset of yellow signal under time pressure conditions was not evaluated in the past. Thus, the current study was designed to examine acceleration behavior and crossing decision of the drivers at the onset of yellow signal under increasing time pressure driving conditions. The data related to acceleration behavior and driver decisions at the onset of yellow signal under time pressure driving conditions can be limited, strenuous, difficult, and unsafe to obtain from the field experiment. Due to this reason, a driving simulator study was performed to collect driving behavior data in a controlled environment. Four signalized intersections with varying scenario configurations were developed on an urban arterial and the data was collected under NTP (baseline), LTP, and HTP driving conditions. Different statistical analysis techniques (explained in section 3.6) were considered and modeling of acceleration behavior and crossing decisions were performed to infer insights from the experiment. Fig. 1 depicts the methodology followed for the current study.

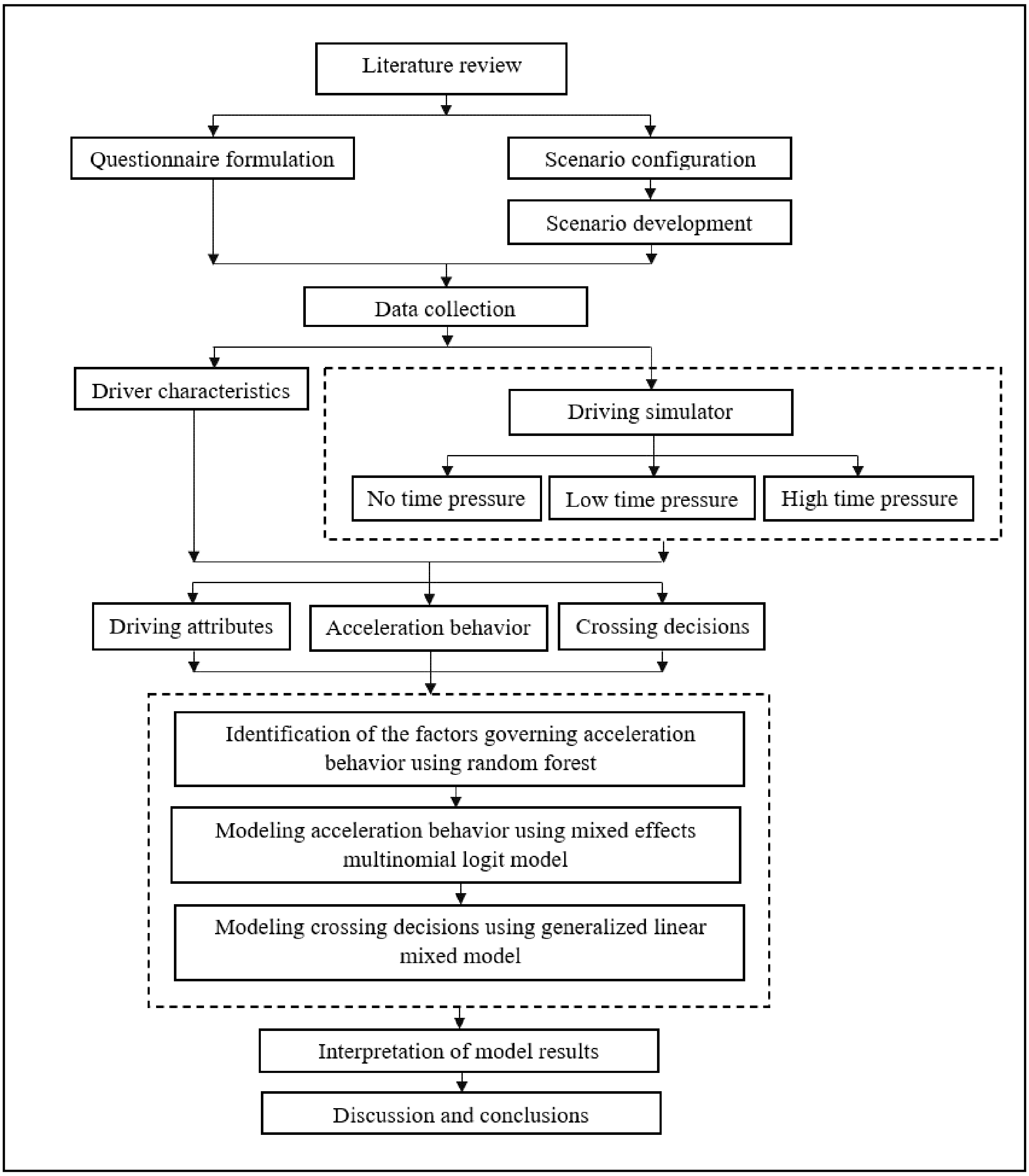


Fig. 1 Flow chart depicting the methodology followed for the current study

3.2 Data collection

This research is a part of larger study focused on examining driving behavior of the drivers under time pressure driving conditions. The traffic events most commonly observed on urban arterial roads such as hazardous situations (pedestrians crossing and obstacle overtaking), car-following, un-signalized intersections and signalized intersections were developed in a driving simulator on a 6 km road for investigating the detrimental effects of time pressure on driving behavior of the drivers (Pawar et al., 2020; Pawar and Velaga, 2020; Pawar and Velaga, 2021a, 2021b). The further details on data collection and analysis related to hazardous events and car-following event can be found in Pawar et al. (2020) and Pawar and Velaga (2021), respectively. The current study analyzes acceleration behavior and crossing decisions of the drivers at signalized intersections. The following sub-sections present description of each component of data collection and data analysis process.

3.3 Driving simulator

A fixed-base open cab driving simulator was used to conduct the experiment. The driving simulator had three LED screens displaying a 150° horizontal field of view. The driving simulator was equipped with completely functioning controls (steering wheel, manual gear box, accelerator, brake, and clutch pedal) and produced simulated traffic and vehicle engine sound. Two different software were available in the driving simulator namely SimVista and SimCreator to develop static and dynamic events, respectively. The driving behavior data was continuously recorded at 120 hz (Choudhary et al., 2020; Pawar and Velaga, 2021b; Yadav and Velaga, 2021, 2020).

3.4 Participants

The sample contained 97 participants aged between 18 to 53 years and their descriptive statistics are presented in Table 2 (Pawar et al., 2020; Pawar and Velaga, 2021a, 2020). The mean age of the participants was 28.49 years (standard deviation: 7.92 years). The sample consisted of 71.13 % male participants and 28.87 % female participants. The mean driving experience and annual mileage of the participants were 7.38 years (standard deviation: 7.16 years) and 26.09 kms/1000 (standard deviation: 45.44 kms/1000), respectively. Among 97 participants, 29 were male professional car drivers working for a private transport company. The participants were investigated about the overnight sleeping hours and exercise habits to examine its influence on driver decisions. The mean overnight sleeping hours of the participants was 6.36 with a standard deviation of 1.84. Around 41 % participants were observed to be physically active (minimum 5 days of physical exercise for at least 30 mins (Haskell et al., 2007)) whereas remaining 59 % reported being physically inactive. Table 2 presents descriptive statistics of the questionnaire data collected from the participants before the start of the actual experiment.

Table 2 Descriptive statistics of the data obtained through questionnaire and driving simulator

Variable (Type)	**Category**	**Mean (SD)**	**Percentage**
Driver demographics			
Age in years (Con)	-	28.49 (7.92)	-
Gender (Cat)	Male	-	71.13
	Female	-	28.87
Physiological characteristics			
Overnight sleeping hours (Con)	-	6.36 (1.84)	-
Regular exercise (Cat)	Yes	-	41.23
	No	-	58.77
Driving history			
Professional driver (Cat)	Yes	-	29.90
	No	-	70.10
Annual mileage in kms/1000 (Con)	-	26.09 (45.44)	-
Simulator output data			
Approach speed in m/s at the onset of yellow signal (Con)	-	18.02 (32.54)	-
Mean acceleration in m/s^2 (Con)	-	-1.88 (1.37)	-
Distance in meters of the driver from the stop line of the intersection (Con)	-	79.33 (52.21)	-
Reaction time in seconds (Con)	-	1.16 (0.83)	-

SD = Standard Deviation; kms = kilometers; Con = Continuous; Cat = Categorical.

3.5 Design of traffic signals

This study focused on analyzing drivers' acceleration behavior and crossing decisions at signalized intersections. A mixed 2*2*2 design was considered for the study. In total, four signalized intersections were designed to study the effects of two distinct time to stop line values (4 s and 6 s) (Choudhary and Velaga, 2019; Pathivada and Vedagiri, 2019) at two different roadways (four-lane and two-lane undivided carriageway) for two types of maneuvers (straight and right-turn). Time to stop line is the time required for a driver to stop the vehicle based on their speed and distance from the stop line at the onset of yellow signal (Haque et al., 2016). Time to stop line is inclusive of yellow signal duration. Time to stop line is considered in driving simulator studies instead of yellow signal duration because drivers are given an equal chance of crossing as well as stopping at the intersection after the onset of yellow signal (Hussain et al., 2020a). The time to stop line values were selected based on literature as presented in Table 1. From Table 1, it can be observed that yellow signal duration throughout the previous studies was in the range of 2 seconds to 4 seconds (Ali et al., 2021; Dogan et al., 2011; Hussain et al., 2020a). Further, various field studies conducted over the years revealed that yellow interval provided in the actual traffic conditions ranged in between 3 seconds to 6 seconds (Mishra and Zhu, 2015; Pathivada and Vedagiri, 2021). Moreover, Manual on Uniform Traffic Control Devices (2009) suggests a yellow change interval in the range of 3 to 6 seconds and Indo-HCM (2017) also advocates 3 seconds of yellow time. Due to all these reasons, 3 seconds of yellow time duration was incorporated in this study. Further, it was observed that drivers mostly stopped at the intersection when they were 3 seconds away from the stop line and crossed the intersection when they were 1 second away from the stop line (Pathivada and Vedagiri, 2021; Rodegerdts et al., 2008). Thus, 3 seconds of yellow signal duration was provided with an additional 1 second and 3 seconds making time to stop line values as 4 seconds and 6 seconds, respectively to study drivers' crossing decisions at signalized intersections under time pressure driving conditions.

It should be noted that India follows left-side driving. Due to this reason, right-turn maneuver becomes critical and thus, was considered in the study. The time to stop line was determined using driver's distance from the stop line and instantaneous speed. A script was programmed in such a way that the traffic signal turned from green to yellow when the estimated time to stop line (ratio of distance from the stop line to the instantaneous speed) was equal to 4 s or 6 s as per the assigned value to that specific intersection (Choudhary and Velaga, 2019). There was no ambient traffic in the vicinity of the signalized intersection. This was done to avoid the interaction between driver and ambient traffic which might influence driver's decision (Ali et al., 2021; Choudhary and Velaga, 2019; Haque et al., 2016). Further, the drivers were not given any prior indication of signal change and were free to take the decision (stop or cross the intersection after the onset of yellow signal) as per their perception and understanding. Fig. 2 illustrates the schematic of signalized intersection as per time to stop line values considered for the current study.

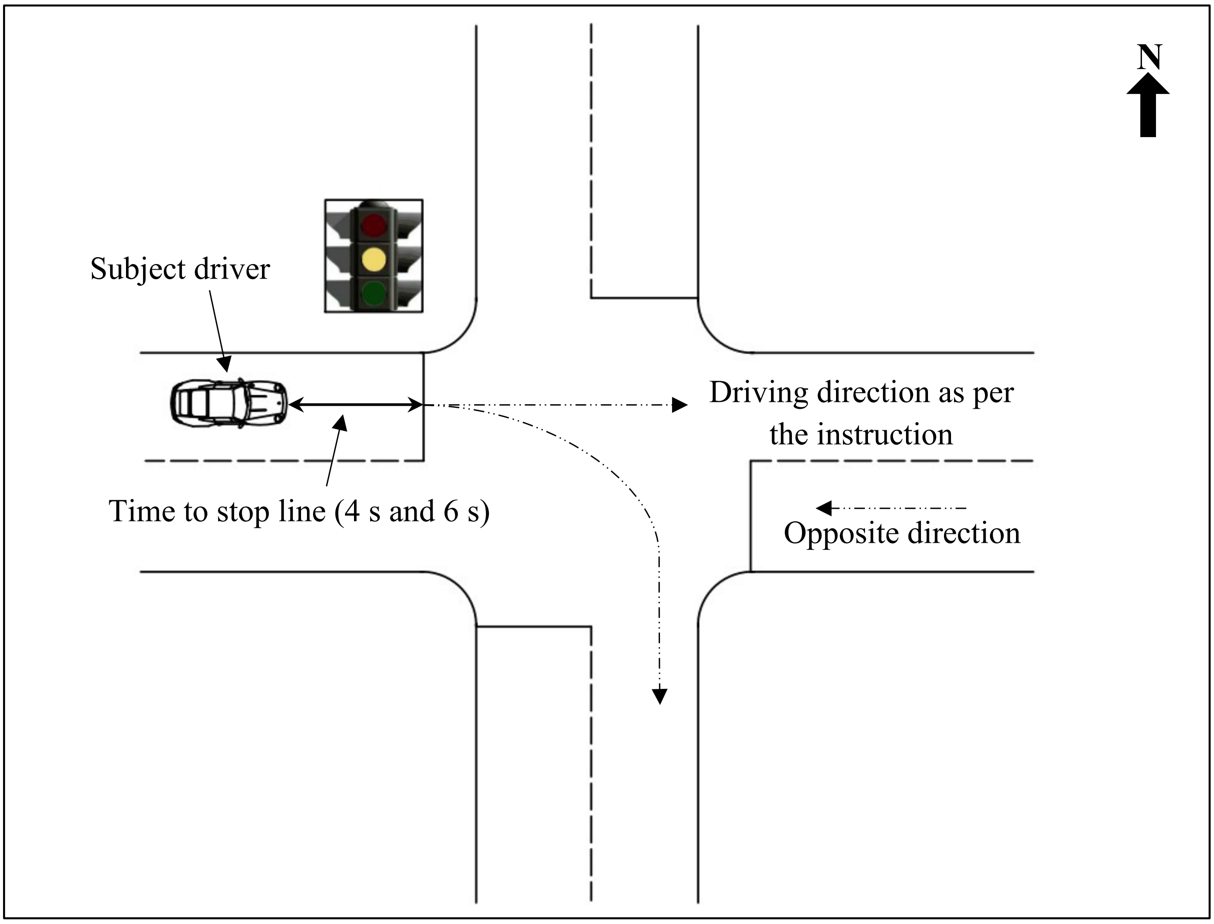


Fig. 2 Schematic of a signalized intersection representing onset of yellow signal when the driver was 4 s and 6 s away from the stop line

3.6 Statistical approach

Three different statistical modeling techniques such as random forest, mixed effects multinomial logit model, and generalized linear mixed model were considered for analyzing drivers' acceleration behavior and crossing decision at signalized intersections. The acceleration behavior was categorized into four different parts (detailed explanation in section 4.1) and random forest model was adopted to identify the explanatory variables governing acceleration behavior (Jahangiri et al., 2016). Further, mixed effects multinomial logit model was incorporated to establish a relationship between acceleration behavior and the significant explanatory variables identified using random forest model (Wu et al., 2017). In the end, drivers' crossing decisions were modeled using generalized linear mixed model for estimating crossing probability with respect to different time pressure driving conditions, acceleration behavior, and other explanatory variables (Choudhary and Velaga, 2020). A 10 % significance level was considered for examining the effects of explanatory variables on acceleration behavior and crossing decisions.

3.6.1 Random forest

A random forest approach, an ensemble learning technique, was used to identify the factors based on variable importance ranking (Breiman, 2001). A random forest model is developed based on two important features: total number of trees in the forest and number of input variables at each split (Yu et al., 2019b). The data is randomly divided into two parts namely training and testing datasets in 70:30 ratio for developing forest and estimating prediction error (Harb et al., 2009). Bootstrap sampling technique is used for drawing samples to develop decision trees from the training dataset (Sarkar et al., 2021). All the decision trees are developed using random feature selection from the drawn samples, also known as bag dataset (Yu et al., 2019a). Finally, the predictions are done using the developed random forest on Out-Of-Bag (OOB) dataset (samples from training dataset which are not used during the development of decision trees) and testing dataset (Breiman, 2001; Ma et al., 2020). The accuracy of the developed random forest model is determined based on the OOB error and prediction error obtained from OOB dataset and testing dataset, respectively (Breiman, 2001; Yang et al., 2019). Generally, a random forest is considered as an appropriate model if the prediction accuracy of testing dataset is more than OOB dataset. In the end, random forest model provides variable importance ranking in terms of permutation importance (Mean Decrease Accuracy) and Gini importance (Mean Decrease Gini) (Jahangiri et al., 2016; Yu et al., 2019a). The Mean Decrease Accuracy is estimated through OOB dataset and displays the degradation of model without each variable. The Mean Decrease Gini is calculated using training dataset and determines the purity of nodes at the end of decision tree without each variable. A higher value for Mean Decrease Accuracy and Mean Decrease Gini indicates that a variable has higher importance in portioning the data into classes (Wu et al., 2017).

The random forest classifier is basically used for dimensionality reduction or feature selection (Widmann and Silipo, 2015; Ye et al., 2018). The feature selection can be easily done through variable importance ranking. High score of mean decrease accuracy and mean decrease Gini indicates that the particular variable plays a substantial role in predicting the outcome

(Widmann and Silipo, 2015). Thus, a random forest classifier is used to predict the likelihood of the dependent variable and parametric regression techniques are used to examine the impact of the input variables on the dependent variable (Wu et al., 2017).

3.6.2 Mixed effects multinomial logit model

A mixed effects multinomial logit model was used to predict the probability of the acceleration behavior (four different categories) during a particular event. Repeated observations were collected from the same drivers in NTP, LTP, and HTP driving conditions. Therefore, mixed effects (fixed and random effects) were considered to incorporate between and within subject variations for predicting the probability of acceleration behavior. A mixed effects multinomial logit model can be expressed as follows (Hedeker, 2003; Wu et al., 2017):

$$p_{ij} = P\left(y_{ij} = \eta \middle| \rho\right) = \frac{exp(\beta_{0\eta} + \beta_{\eta} X_{ij\eta} + V_{ij\eta} + \varepsilon_{ij\eta})}{1 + \sum_{\gamma} exp(\beta_{0\gamma} + \beta_{\eta} X_{ij\gamma} + V_{ij\gamma} + \varepsilon_{ij\gamma})} (\forall \eta \neq \gamma) \quad (1)$$

where, y is the dependent variable, P is the probability of i^{th} participant (1 to 97) in j^{th} time pressure driving condition, η is the category of acceleration behavior, ρ is the random effects, β is the parameter estimate, V_{ij} is the vector of random disturbances and ε_{ij} is the random error independently and identically distributed (Wu et al., 2017). The parameter estimates for mixed effects multinomial logit model were determined using iterative maximum likelihood solution.

3.6.3 Generalized linear mixed model

A generalized linear mixed model was considered for estimating the probability of crossing decision according to acceleration behavior and time to stop line under time pressure driving conditions. The mixed effects were considered for obtaining unbiased estimates in the model due to repeated data collection (Gupta et al., 2021; Mannering et al., 2016). A generalized linear mixed model can be formulated as follows (Yadav and Velaga, 2019):

$$g\left(y_{ij}\right) = \beta_0 + \beta * X_{ij} + V_{ij} + \varsigma_{ij} \quad (3)$$

where, g is the link function ς is the unobserved random error with mean zero and constant variance (Xiong et al., 2007).

A logit link function is generally used to establish a relationship between dependent variable and explanatory variables for a binary response as shown below (Choudhary and Velaga, 2018):

$$log\left[\frac{P\ (y_{ij}=1)}{1-P\ (y_{ij}=1)}\right] = \beta_0 + \beta * X_{ij} + V_{ij} + \varsigma_{ij} \tag{4}$$

where, log is the natural logarithm. Thus, probability can be estimated as follows:

$$P\ (y_{ij} = 1) = \frac{1}{1 + exp-(\beta_0 + \beta * X_{ij} + V_{ij})} \tag{5}$$

The crossing decision was a binary variable where y =1 was considered for crossing decision and y = 0 was considered for stopping decision. The parameter estimates for GLM model were determined using maximum simulated likelihood approach (Drukker, 2006).

4. Data analysis and results

4.1 Acceleration behavior of the drivers after the onset of yellow signal under time pressure

The current study attempts to explore the impact of different time pressure driving conditions on acceleration behavior of the drivers while driving through a signalized intersection when the signal turns from green to yellow. Thus, the acceleration behavior was observed from the point when the drivers reacted to the change in traffic signal from green to yellow. The acceleration behavior was categorized into four different parts as nominal variable: (a) continuous deceleration (drivers continuously decelerating till they stop the vehicle); (b) acceleration-deceleration (drivers initially accelerating but finally decelerating to stop the vehicle); (c) deceleration-acceleration (drivers initially decelerating but finally accelerating to cross the intersection); and (d) continuous acceleration (drivers continuously accelerating to cross the intersection). The driver's accelerator pedal and brake pedal applications were assessed simultaneously for extracting acceleration behavior data. Application of accelerator pedal was considered as acceleration and release of accelerator pedal with application of brake pedal was considered as deceleration. In total, 1,164 encounters were observed at four signalized intersections for three different time pressure driving conditions from 97 participants. There were 874 (75 %), 109 (9 %), 113 (10%), and 68 (6%) continuous deceleration, acceleration-deceleration, deceleration-acceleration, and continuous acceleration encounters, respectively during NTP, LTP, and HTP driving conditions as shown in Fig. 3.

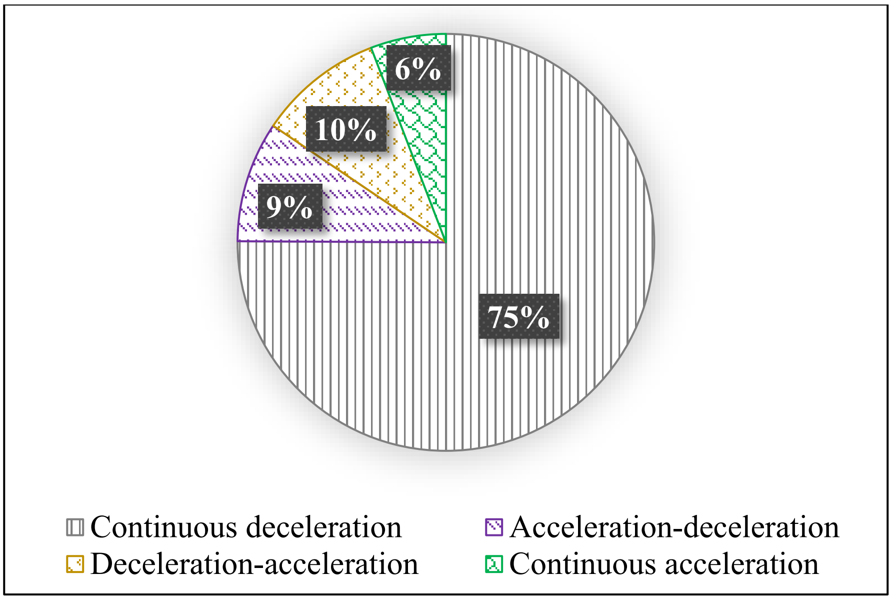


Fig. 3 Percentage of different acceleration encounters observed throughout the experiment.

4.2 Explanatory variables

The explanatory variables or input variables can be divided into five broad categories: driver demographics and driving history, physiological characteristics, driving condition, scenario configuration, and driving attributes. The details of the variables as per each category are presented below:

Driver demographics and driving history: Driver's age, gender, driving profession, driving experience, and annual mileage were considered under this category.

Physiological characteristics: Driver's exercise habits and overnight sleeping hours were considered under this category.

Driving condition: This particular factor accounted the effect of time pressure imposed on the drivers in the form of NTP, LTP, and HTP.

Scenario configuration: The different configurations of the signalized intersections such as time to stop line (4 s vs 6 s), type of maneuver (right turn vs straight), and number of lanes (two-lane vs four lane) were considered in this category.

Driving attributes: Approach speed, reaction time, mean acceleration (measured from the point when the drivers reacted to change in signal from green to yellow), and distance to stop line of the intersection were considered under this category.

4.3 Identification of the factors governing acceleration behavior using random forest approach

Overall, the current study had 1,164 valid samples from which 821 samples were randomly selected for training dataset and remaining 343 samples were selected for testing dataset. Initially, all 15 input variables (described in section 4.2) were considered while developing random forest model. This was done because the random forest model can mitigate the multicollinearity issue and effectively use the variables using random feature selection (square root of total number of variables at each split) and numerous decision trees (Yu et al., 2019b). Thus, at the initial stage, a random forest model was developed, which comprised of 1,000 decision trees and 3 input variables at each split and the prediction results are presented in Table 3. The OOB error rate was 18.25 % providing an accuracy of 81.75 % while predicting acceleration behavior of the drivers. The testing dataset provided an accuracy of 80.41 %. The overall analysis indicated that the developed random forest model provides decent accuracy while predicting the acceleration behavior, however, the model can be further improvised by tuning number of decision trees and input variables. Thus, the class error and OOB error was estimated for different combinations of decision trees and input variables. It was observed that class error was constant after 900 decision trees and the OOB error was lowest for 6 input variables. Therefore, a new random forest model was developed with 900 decision trees and 6 input variables at each split and the results are presented in Table 4

The OOB error of the improvised random forest model was 17.64 %, i.e., the accuracy was 82.36 %. Further, the prediction accuracy through testing dataset increased from 80.41 % to 83.09 %. Thus, it can be concluded that the improvised random forest model with 900 decision trees and 6 input variables performs well while predicting acceleration behavior of the drivers. Finally, the variable importance ranking was estimated with two measures, Mean Decrease Accuracy and Mean Decrease Gini as shown in Fig. 4. The variable importance ranking signified the accuracy of the model performance associated with each variable. Generally, the variables with Mean Decrease Accuracy and Mean Decrease Gini values less than 10 are considered having very low influence and can be eliminated from the model (Yu et al., 2019b). It can be observed that all the variables had Mean Decrease Accuracy (Fig. 4a) and

Mean Decrease Gini (Fig. 4b) values more than 10. This represented the significance of the input variables while predicting acceleration behavior. The mean acceleration and approach speed ranked top two in both the measures indicating their importance while predicting acceleration behavior. Apart from these two variables, time pressure driving conditions, reaction time, driver's distance from the intersection when the signal turned from green to yellow, time to stop line, driving experience, and age significantly influenced the prediction of acceleration behavior. Thus, all these variables can be considered for modeling acceleration behavior using mixed effects multinomial logit model.

Table 3 Confusion matrix for prediction of acceleration behavior using random forest model

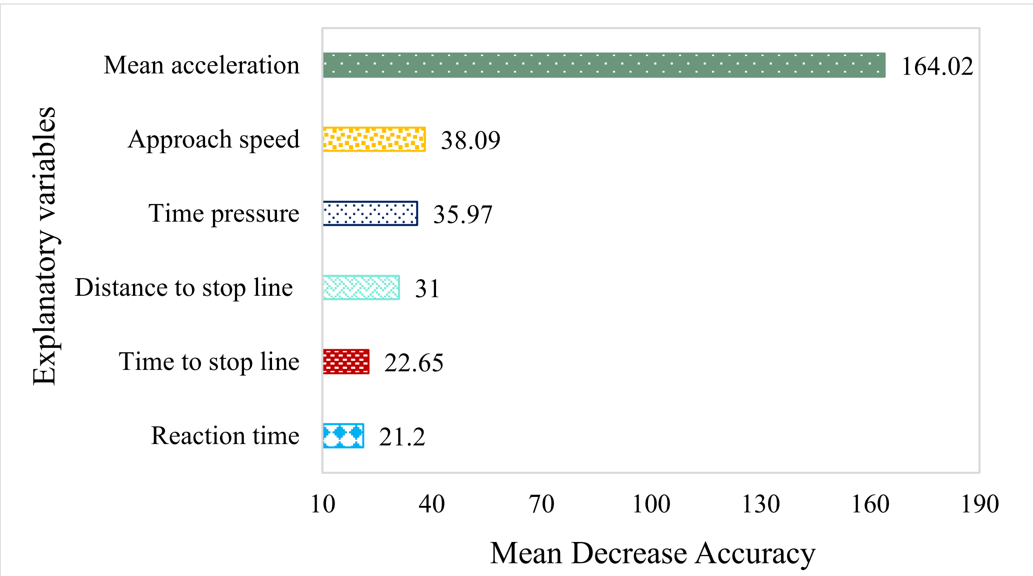
Training set							
Predicted	**CD**	**AD**	**DA**	**CA**	**Class error**	**OOB Error rate**	**Accuracy**
CD	614	5	2	2	0.014	18.25 %	81.75 %
AD	41	13	7	12	0.82		
DA	44	4	17	13	0.78		
CA	4	10	6	28	0.41		
Testing set							
Predicted	**CD**	**AD**	**DA**	**CA**	**Class error**	**Accuracy**	**Confidence interval**
CD	251	21	26	0	0.15	80.41 %	75.80 %, 84.48 %
AD	0	6	3	1	0.40		
DA	0	3	4	5	0.66		
CA	0	6	2	14	0.36		

CD = Continuous Deceleration; AD = Acceleration-Deceleration; DA = Deceleration-Acceleration; CA = Continuous Acceleration; OOB = Out-Of-Bag.

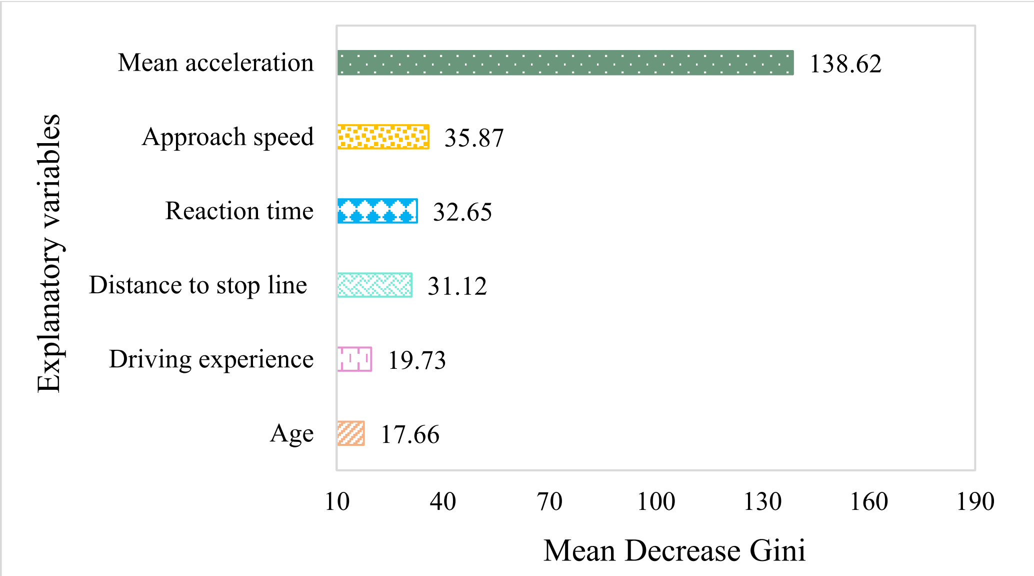
Table 4 Confusion matrix for prediction of acceleration behavior using random forest model with 900 decision trees and 6 input variables

Training set							
Predicted	**CD**	**AD**	**DA**	**CA**	**Class error**	**OOB Error rate**	**Accuracy**
CD	611	5	5	2	0.019	17.64%	82.36%
AD	37	11	12	13	0.84		
DA	34	6	24	14	0.69		
CA	1	9	7	31	0.35		
Testing set							
Predicted	**CD**	**AD**	**DA**	**CA**	**Class error**	**Accuracy**	**Confidence interval**
CD	251	18	21	0	0.13	83.09%	78.64%, 86.86%
AD	0	10	1	1	0.16		
DA	1	2	11	6	0.45		
CA	0	6	2	13	0.38		

CD = Continuous Deceleration; AD = Acceleration-Deceleration; DA = Deceleration-Acceleration; CA = Continuous Acceleration; OOB = Out-Of-Bag.



(a)



(b)

Fig. 4 Variable importance ranking in terms of (a) Mean Decrease Accuracy and (b) Mean Decrease Gini

4.4 Modeling acceleration behavior using mixed effects multinomial logit model

A mixed effects multinomial logit model was considered to analyze four distinct variations observed in acceleration behavior (Li et al., 2020; Pani et al., 2020; Wu et al., 2017). Continuous deceleration was considered as the reference category for modeling acceleration behavior using mixed effects multinomial logit model. The explanatory variables ranking in descending order of importance, obtained through random forest's variable importance analysis were involved in acceleration behavior prediction model. Table 5 presents the estimation results of the mixed effects multinomial logit model with goodness of fit. Time pressure driving conditions (NTP as reference category), Time to stop line (6 s as reference category), and mean acceleration were observed to have significant impact on different acceleration behavior of the drivers. It is interesting to observe that the coefficients of the model for deceleration-acceleration, acceleration-deceleration, and continuous acceleration had same effect with different magnitude. The intercept of the model results had negative effect on acceleration behavior. This signified that the possibility of encountering deceleration-acceleration, acceleration-deceleration, and continuous acceleration as compared to continuous deceleration when the signal changed from green to yellow were 43 %, 44 %, and 40.3%, respectively.

Further, the model results revealed that drivers adopting acceleration-deceleration behavior instead of continuous deceleration behavior was higher under LTP (70%) than HTP (63%) driving conditions. The likelihood of drivers undergoing deceleration-acceleration and continuous acceleration rather than continuous deceleration patterns were higher during HTP than LTP driving conditions. In general, there were high chances of encountering deceleration-acceleration (123%) as compared to continuous acceleration (77%) and acceleration-deceleration (63.5%) in lieu of continuous deceleration behaviors under HTP driving condition when the signal turned from green to yellow. The mean acceleration showed substantial positive effect while predicting acceleration behavior. It can be observed that 1 m/s^2 increment in mean acceleration increased the odds of encountering acceleration-deceleration, deceleration-acceleration, and continuous acceleration rather than continuous deceleration behaviors by 46%, 47%, and 60%, respectively. Moreover, the odds of driver adopting deceleration-acceleration, continuous acceleration, and acceleration-deceleration over continuous deceleration were lower by 35%, 33%, and 26%, respectively when TSL was 6 s than 4 s. Other explanatory variables (irrespective of variable importance ranking) showed no significant effect on acceleration behavior under different time pressure driving conditions.

Table 5 A mixed effects multinomial logit model results for predicting acceleration behavior (reference: continuous deceleration)

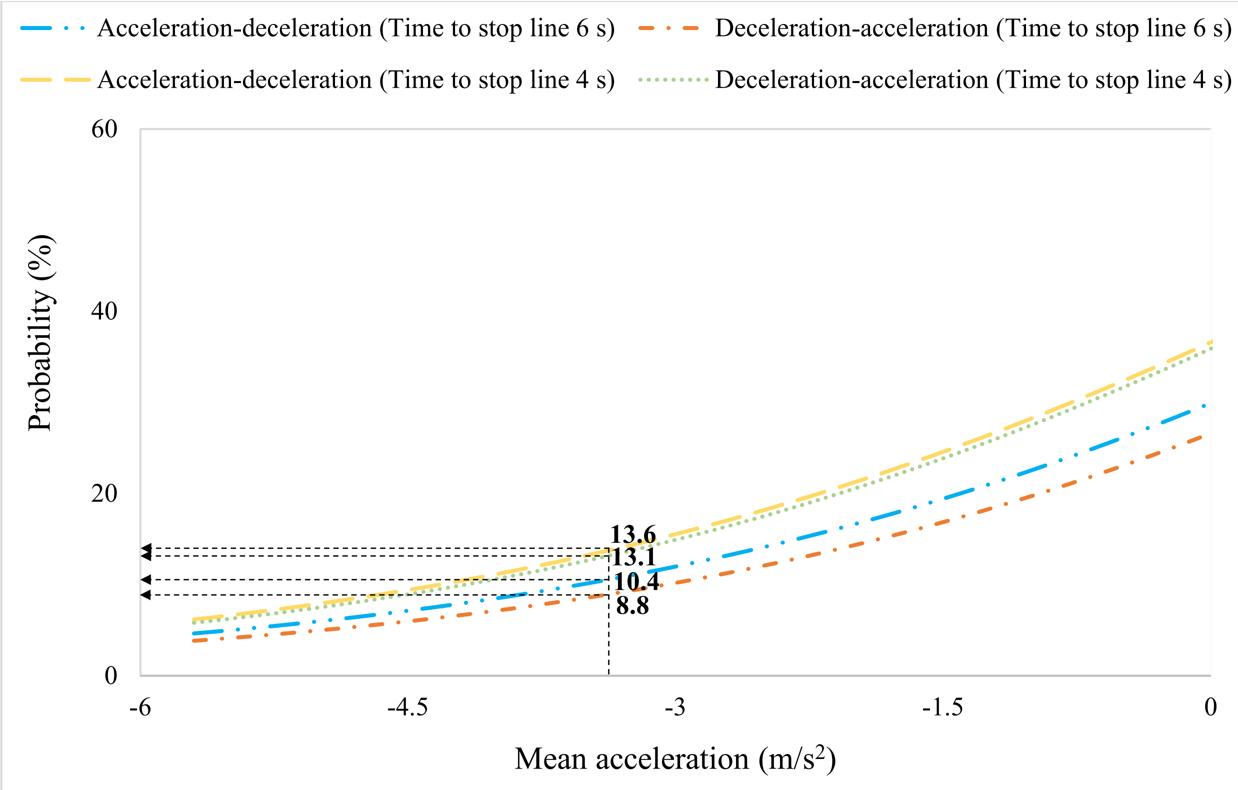
	Acceleration-deceleration				Deceleration-acceleration				Continuous acceleration			
Parameters	**β**	**Exp(β)**	**SE**	**t-stat**	**β**	**Exp(β)**	**SE**	**t-stat**	**β**	**Exp(β)**	**SE**	**t-stat**
Intercept	-0.55	0.58	0.19	-2.89***	-0.58	0.56	0.19	-3.02***	-0.51	0.60	0.19	-2.64***
LTP	0.53	1.70	0.20	2.54**	0.54	1.72	0.21	2.50**	0.48	1.62	0.22	2.20**
HTP	0.49	1.63	0.20	2.31**	0.80	2.23	0.21	3.82***	0.57	1.77	0.22	2.59**
Mean acceleration	0.38	1.46	0.16	5.92***	0.39	1.47	0.06	6.11***	0.47	1.60	0.06	6.92***
Time to stop line: 6 s	-0.30	0.74	0.064	-1.793*	-0.43	0.65	0.16	-2.59**	-0.40	0.67	0.17	-2.28**

Goodness-of-fit

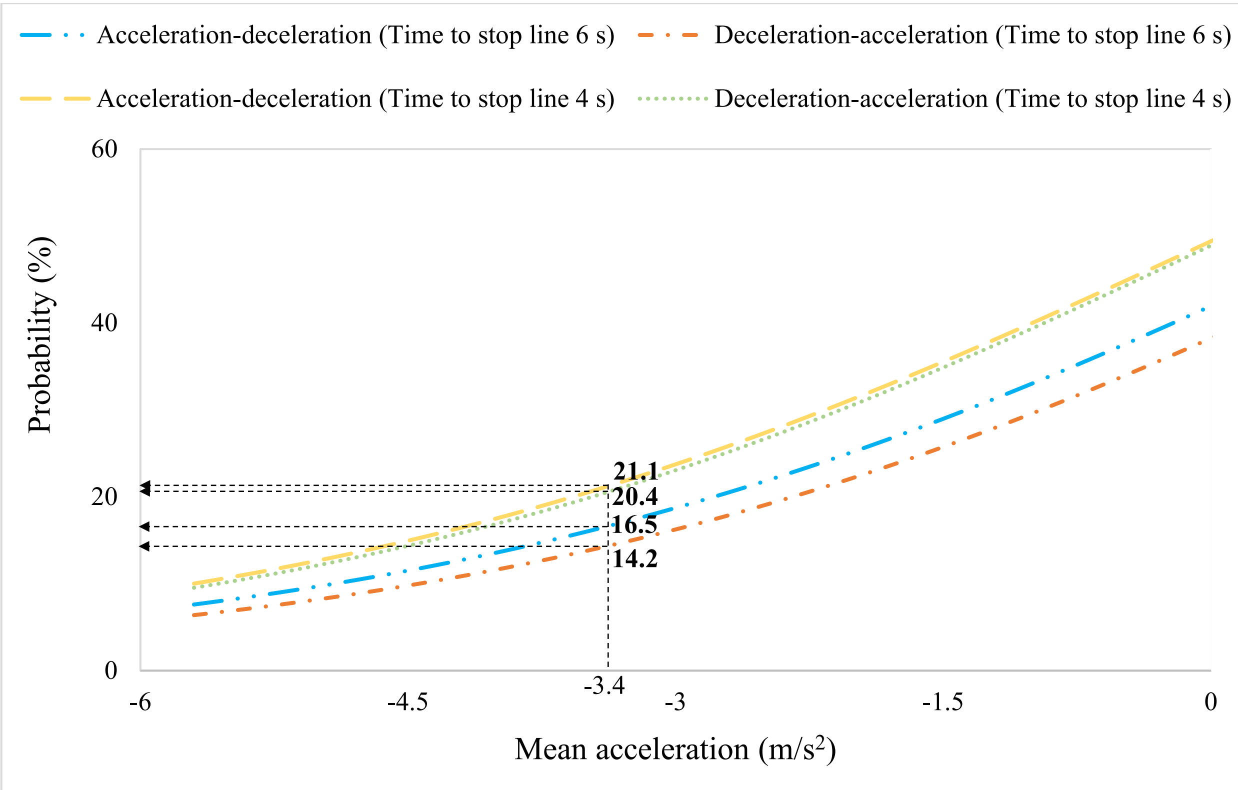
-2 log pseudo likelihood	AICC	BIC
9,506.77	9,512.79	9,527.91

*β = Estimate; Exp = Exponential; SE = Standard Error; LTP = Low Time Pressure; HTP = High Time Pressure; AICC = Akaike Information Corrected Criterion; BIC = Bayesian Information Criterion; *p < 0.10; **p < 0.05; ***p < 0.01.*

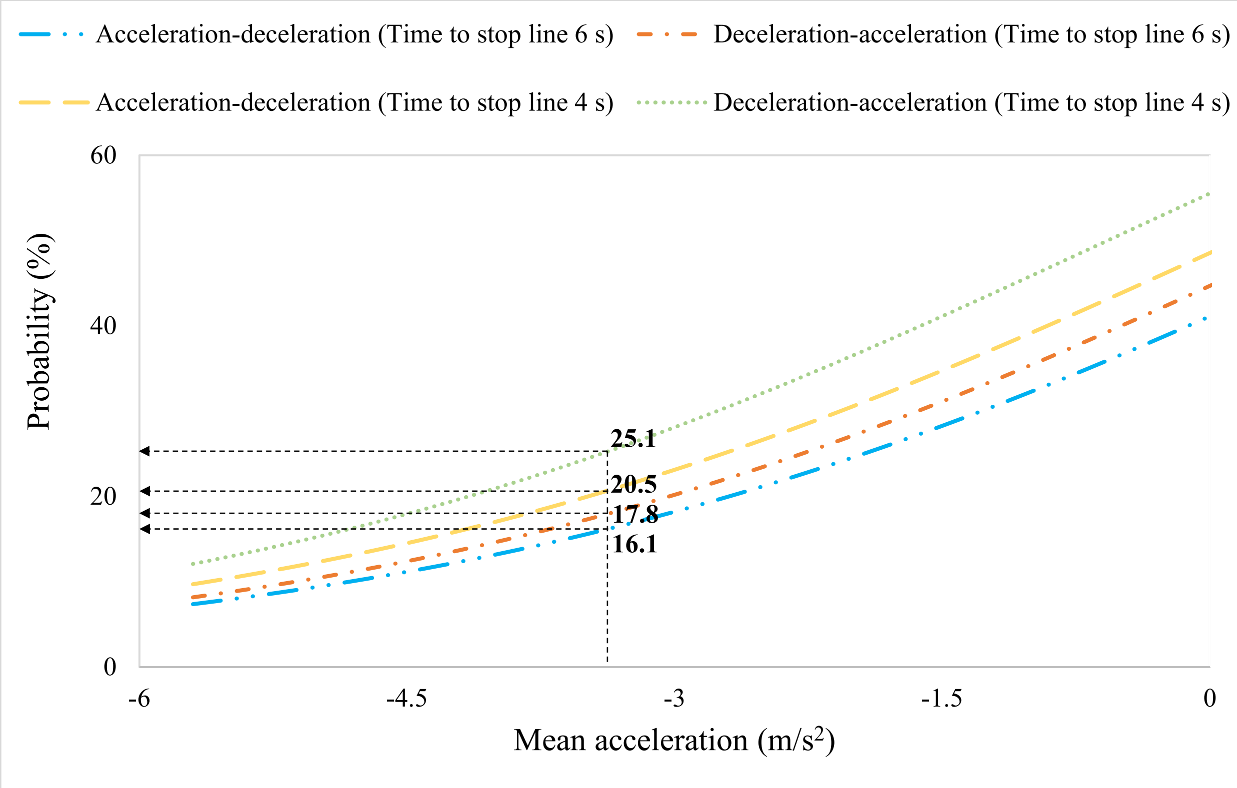
Fig. 5 was plotted to acquire better insights on acceleration-deceleration and deceleration-acceleration behaviors with respect to continuous deceleration behavior. According to AASHTO (2011), most of the vehicle-braking systems are capable of providing a comfortable deceleration rate of 3.4 m/s^2. Numerous studies documented in the literature suggested a threshold of 3.4 m/s^2 for comfortable deceleration to stop the vehicle (Guido et al., 2012; Kuang and Qu, 2014; Mahmud et al., 2017; Tomar et al., 2020). Therefore, acceleration-deceleration and deceleration-acceleration behaviors were compared at -3.4 m/s^2 mean acceleration. It can be observed that drivers under NTP and LTP driving conditions with mean acceleration of -3.4 m/s^2 when time to stop line was 6 s were more likely to exhibit acceleration-deceleration (10.4 %) than deceleration-acceleration (8.8 %) behaviors instead of continuous deceleration behavior as shown in Fig. 5a and Fig. 5b, respectively. No significant difference can be observed in between acceleration-deceleration (13.6 %) and deceleration-acceleration (13.1 %) probabilities under NTP and LTP driving conditions when the drivers were 4 s away from the intersection (Fig. 5a and Fig. 5b). Further, acceleration behavior of the drivers varied significantly under HTP driving condition. The drivers under HTP were observed to undergo deceleration-acceleration behavior as compared to acceleration-deceleration and continuous deceleration behaviors as shown in Fig. 5c. The drivers under HTP had high likelihood of adopting deceleration-acceleration behavior when time to stop line was 4 s than 6 s. From Fig. 5c, it can be observed that the odds of drivers adopting deceleration-acceleration behavior (25.1 % and 17.8 % when time to stop line were 4 s and 6 s, respectively) over acceleration-deceleration behavior (20.5 % and 16.1 % when time to stop line were 4 s and 6 s, respectively) were substantially higher under HTP driving condition. Thus, it can be clearly understood that driving strategy of the drivers altered as per time pressure driving conditions and time to stop line at signalized intersections.


Acceleration-deceleration (Time to stop line 6 s)
Deceleration-acceleration (Time to stop line 6 s)
Acceleration-deceleration (Time to stop line 4 s)
Deceleration-acceleration (Time to stop line 4 s)
Probability (%)
60
40
20
0
13.6
13.1
10.4
8.8
-6
-4.5
-3
-1.5
0
Mean acceleration (m/s²)

(a)


Acceleration-deceleration (Time to stop line 6 s)
Deceleration-acceleration (Time to stop line 6 s)
Acceleration-deceleration (Time to stop line 4 s)
Deceleration-acceleration (Time to stop line 4 s)
Probability (%)
60
40
20
0
21.1
20.4
16.5
14.2
-3.4
-6
-4.5
-3
-1.5
0
Mean acceleration (m/s²)

(b)



(c)

Fig. 5 Graphical representation of drivers' acceleration-deceleration and deceleration-acceleration behaviors in terms of continuous deceleration behavior under (a) NTP, (b) LTP, and (c) HTP driving conditions

4.5 Modeling crossing decisions

Throughout the driving session, there were 875 stop decisions and 289 cross decisions at signalized intersections as mentioned in section 4.1. All the drivers adopting continuous acceleration were found to cross the intersection (23.18 % of total cross decisions) whereas 39.10 %, 32.52 %, and 5.2 % of the total crossing decisions were observed during deceleration-acceleration, acceleration-deceleration, and continuous deceleration behaviors. On the other hand, 98.17 % of the total stop decisions were due to drivers' continuous deceleration and the remaining 1.83 % stop decisions comprised of acceleration-deceleration (1.71 %) and deceleration-acceleration (0.12 %) encounters. Here, it should be noted that around 2 % drivers undergoing continuous deceleration failed to stop before the stop line of the intersection. The possible reason might be the inadequate deceleration after the onset of yellow signal. The drivers failing to stop before the stop line of the intersection might have decided to cross the intersection due to the intuition of unsafe driving environment while stopping the vehicle after crossing stop line of the intersection (Choudhary and Velaga, 2020).

Drivers' crossing decisions were analyzed using Generalized Linear Mixed (GLM) model with logit link function and the results are presented in Table 6. The GLM model results revealed that the likelihood of crossing a signalized intersection increased by 2.73 times and 4.26 times when the drivers were under LTP and HTP driving conditions, respectively as compared to NTP driving condition. Further, the probability of stopping reduced by 7.02 and 10.20 when the drivers adopted acceleration-deceleration and deceleration-acceleration patterns in lieu of continuous deceleration. The crossing probability was also influenced by time to stop line and age. The odds of crossing the signalized intersection reduced by 62 % when the signal turned from green to yellow 6 seconds prior to the stop line of the intersection. Moreover, the crossing probability reduced by 74 % with every 1-year increment in age.

Fig. 6 represents crossing probability of the drivers according to acceleration behavior, time pressure driving conditions, and drivers' age. It can be observed that crossing probability decreased continuously with increment in age. Thus, it can be anticipated that the crossing probability will continuously decrease beyond the age limit considered in this study. The crossing probability of the drivers adopting deceleration-acceleration behavior was more when time to stop line was 4 s than 6 s as shown in Fig. 6. Further, a substantial decrement in crossing probabilities can be observed with increment in age when the drivers adopted acceleration-deceleration behavior instead of deceleration-acceleration behavior. This implied that the effect of signal change from green to yellow was relatively more acute with increment in age when time to stop line was 6 s than 4 s steering drivers to adopt acceleration-deceleration behavior instead of deceleration-acceleration behavior.

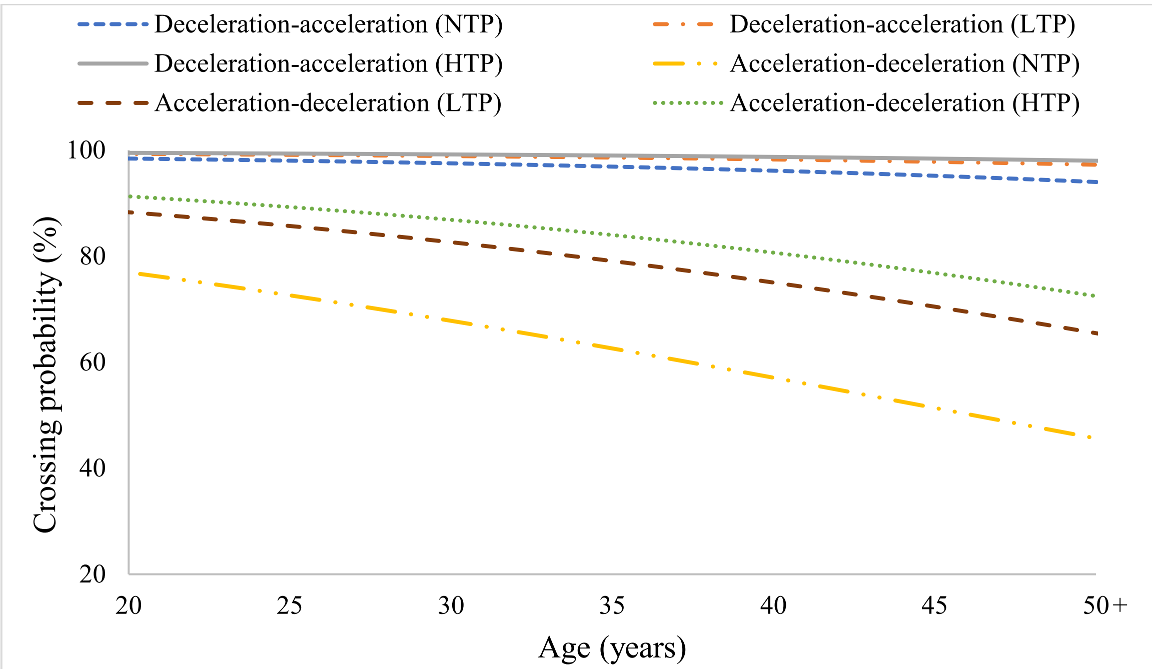
Table 6 Estimates of generalized linear mixed model for crossing probability at signalized intersections

Parameters	**Estimate (β)**	**Exp(β)**	**SE**	**z-value**
Intercept	-4.34	0.01	0.70	-6.16***
LTP	1.01	2.73	0.56	1.79*
HTP	1.45	4.26	0.55	2.62***
Acceleration-deceleration	7.02	1119.90	0.72	9.69***
Deceleration-acceleration	10.20	27038.04	1.28	7.91***
Time to stop line: 6 s	-0.94	0.38	0.43	-2.18**
Age	-1.31	0.26	0.57	-2.27**

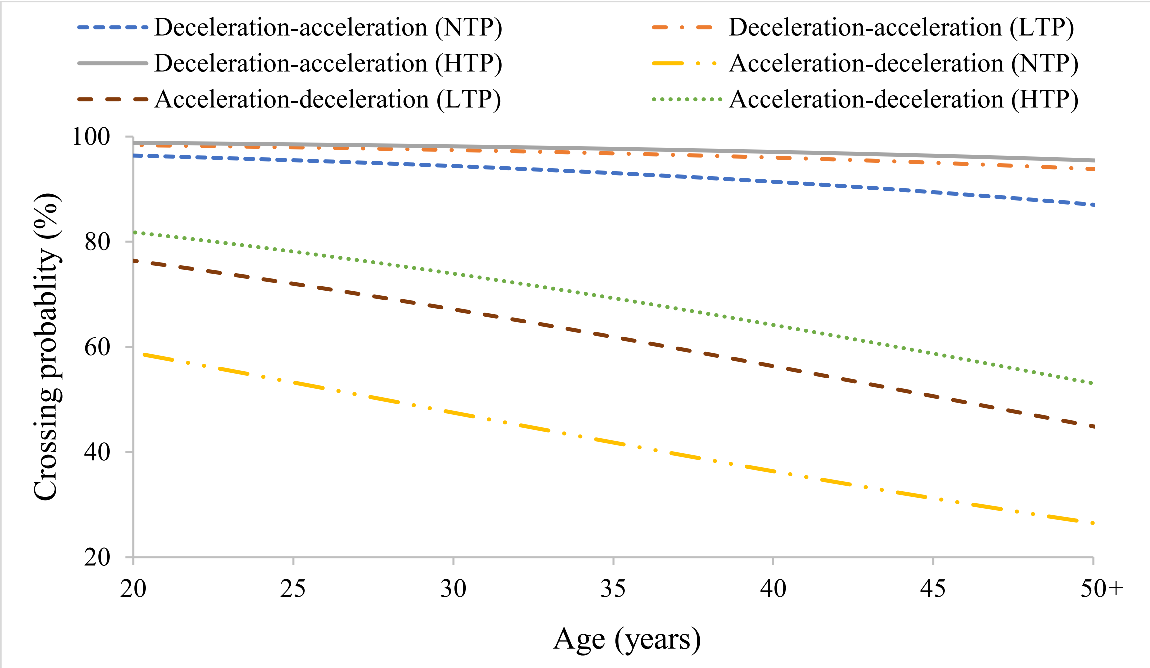
Goodness-of-fit of the model

df	Log-likelihood	AIC	BIC
8	-110.78	237.57	277.57

*Exp=Exponential; SE=Standard Error; df=degrees of freedom; AIC=Akaike Information Criterion; BIC=Bayesian Information Criterion; *p < 0.10; **p < 0.05; ***p < 0.01.*



(a)



(b)

Fig. 6 Crossing probability of the drivers according to age while adopting acceleration-deceleration and deceleration-acceleration behaviors when time to stop line was (a) 4 s and (b) 6 s under time pressure driving conditions

5. Discussion

The current study investigated acceleration behavior and crossing decision of the drivers at the onset of yellow signal under increasing time pressure driving conditions. The acceleration behavior of the drivers was characterized into four distinct categorizes. Random forest model was used to identify the factors influencing acceleration behavior of the drivers. The identified factors were used as explanatory variables in mixed effects multinomial logit model for predicting acceleration behavior. In the end, a generalized linear mixed model was developed for estimating crossing probability of the drivers according to time pressure driving conditions, acceleration behavior, and gender.

The random forest model revealed that driving attributes such as approach speed, reaction time, and distance to stop line of the intersection showed significant effect on acceleration behavior of the drivers. Previous research revealed that drivers who were near to the intersection stop line with high approach speed, reacted swiftly to cross the intersection when the signal turned from green to yellow. Here, it should be noted that high driving speed will result in lower acceleration capability of the vehicle which might influence driver's decision forcing him/her to alter acceleration behavior (Palat and Delhomme, 2016). The research conducted by Lee et al. (2002) showed that swift reaction to the event provides driver with additional time to evaluate his/her decision and accordingly alter driving behavior (Lee et al., 2002). Nevertheless, numerous studies showed that drivers near to the intersection, driving at high speed were more likely to cross the intersection (Choudhary and Velaga, 2019; Haque et al., 2016; Pathivada and Vedagiri, 2019). This can be attributed to the fact that drivers may end up in the dilemma zone, where they cannot safely stop at the intersection due to the high driving speed and inadequate space availability for halting the vehicle before the stop line of the intersection (Ali et al., 2021; Elmitiny et al., 2010).

The random forest model showed that mean acceleration was the most important input factor for predicting acceleration behavior. The acceleration behavior was characterized into four distinct categorizes by simultaneously observing accelerator pedal and brake pedal application after the driver's reaction to the onset of yellow signal. The mean acceleration values were also extracted from the point when the drivers reacted to change in signal from green to yellow. Thus, mean acceleration values were representative of acceleration behavior. A random forest model was developed without mean acceleration and very low prediction accuracy was observed. Further, in reality, it is not possible to directly obtain the change in acceleration behavior (for example acceleration-deceleration or deceleration-acceleration behaviors). Nevertheless, mean acceleration of the drivers can be easily recorded. Due to these reasons, mean acceleration was considered while modeling acceleration behavior of the drivers.

The mixed effects multinomial logit model result revealed that drivers with mean deceleration rate of 3.4 m/s^2 had around 89 – 91 %, 83 – 85 %, 82 – 84 % likelihood of adopting continuous deceleration behavior under NTP, LTP, and HTP driving conditions, respectively when they were 6 s away from the intersection. Similarly, the possibility of adopting continuous deceleration behavior with mean deceleration of 3.4 m/s^2 under NTP, LTP, and HTP driving conditions when the drivers were 4 s away from the intersection were 86 – 87 %, 79 – 80 %, 75 – 79 %, respectively. Thus, it can be concluded that drivers had 75 – 91 % possibility of adopting continuous deceleration when the mean deceleration was 3.4 m/s^2 to comfortably stop the vehicle. Further, previous literature on signalized intersection revealed that deceleration rate and crossing probability decreased with increment in time to stop line values. The stopping probability (100 - crossing probability) of the drivers adopting continuous deceleration were

98.72 %, 96.59 %, and 94.77 % under NTP, LTP, and HTP driving conditions, respectively when they were 4 s away from the intersection. The stopping probability increased up to 99.50 %, 98.64 %, and 97.90 % under NTP, LTP, and HTP driving conditions, respectively when the drivers were 6 s away from the intersection. Thus, it can be concluded that drivers who were far from the intersection were more likely to adopt continuous deceleration to stop at the intersection.

In the current study, female drivers showed high likelihood of crossing the intersection as compared to male drivers. The study conducted by Ali et al. (2021) and Haque et al. (2016) revealed that female drivers were less likely to stop at the onset of yellow signal. The current study showed that male drivers were quick to react to the signal change (green to yellow) as compared to female drivers ($t(525.45) = 3.69$; p-value < 0.01). Thus, slow response of female drivers to signal change might be the reason behind high crossing probability than male drivers (Haque et al., 2016).

6. Conclusions

This study examined three research hypotheses as stated in section 2.4. The mixed effects multinomial logit model and generalized linear mixed model results indicated that time pressure had a significant effect on acceleration behavior and crossing decision of the drivers at the onset of yellow signal. The driver decisions were also observed to vary significantly as per time to stop line values and driver demographics. Based on the results obtained through this study, it can be concluded that time pressure alters acceleration behavior of the drivers leading to risky driving decisions which can have serious safety critical situations as compared to normal driving. Therefore, drivers should be made aware of severe consequences of involving in deliberate or accidental red-light violations resulting from crossing decisions taken during the onset of yellow signal. Further, it is advisable that drivers should gradually stop at signalized intersection after the onset of yellow signal, irrespective of driving condition, to avoid hazardous traffic situations (Mathew, 2009).

7. Research contribution and implication

The current study contributed to the existing literature in four main facets:

(i) As per the authors' best knowledge, this is the first study that evaluated the influence of increasing time pressure driving conditions on acceleration behavior and crossing decision at signalized intersections. Most of the existing studies directly evaluated drivers' crossing decision without considering possible implications of acceleration behavior. Thus, the current research work makes a significant contribution to the existing literature by modeling acceleration behavior which can be effectively used for predicting crossing probability of the drivers.

(ii) This study provides insights on crossing probabilities in normal and time pressure driving conditions. The results obtained through this study can be used to augment the design of traffic signal timings (yellow and all red timings). This can be achieved by identifying the neighborhood with various types of built-up environments (commercial, corporate, residential, recreational, etc.), socio-demographics, and transportation infrastructure. The yellow and all red signal timings of the particular area having high chances of drivers driving under time pressure can be investigated based on research methodology followed in the current study and modified by performing similar analysis.

(iii) It is extremely difficult to detect acceleration behavior of the drivers in real-time or naturalistic studies. The developed mixed effects multinomial logit model showed that acceleration behavior can be successfully predicted using mean acceleration and time to stop line values after the onset of yellow signal. Various studies showed that drivers experience high dilemma when they were around 6 seconds away from the stop line of the intersection (Pathivada and Vedagiri, 2021; Rakha et al., 2008). Thus, driving strategies can be developed in terms of acceleration behavior for minimizing abrupt acceleration-deceleration rates to reduce waiting time at intersections using Model Predictive Control (MPC) and Vehicle- to-Infrastructure (V2I) communication systems (He et al., 2021; Ubiergo and Jin, 2016). The MPC system can estimate the required acceleration by collecting information of traffic signal timing from V2I system and develop driving strategy for stopping or crossing the intersection when the drivers are around 6 seconds away from the stop line of the intersection (Butakov and Ioannou, 2016; He et al., 2021).

(iv) Most of the signalized intersections in India are without countdown timer because of which drivers are subjected to sudden change in traffic signal. Normal reaction time considered in transportation research is 2.5 seconds whereas yellow signal provides 3 seconds to take a decision (AASHTO, 2011; Indian Road Congress, 1976; Pathivada and Vedagiri, 2019). Thus, a particular driver has only 0.5 seconds for implementing his/her decision. From the current study, it can be understood that drivers react within 1.5 seconds irrespective of driving condition and driver demographics. The swift reaction from the drivers might be due to the fact that they are habitual to the sudden signal change and have developed themselves to take quick decisions (Pawar and Velaga, 2020).

8. Study limitations and future scope

The current study has some limitations which restrict generalization of the results. 3 s yellow signal duration was fixed for the current study. In future, researchers can vary the yellow signal duration to check its influence on acceleration behavior and crossing decision under time pressure driving conditions. The study invited all the eligible participants; however, the sample was dominated by male drivers as compared to female drivers. This might be due to the fact that India has very low female driving population (Ministry of Road Transport & Highways, 2019). Further, drivers above the age of 60 years experienced simulator sickness and therefore were excluded from the study. The data collection was conducted in the fixed order of NTP, LTP, and HTP driving conditions. The fixed order of data collection is considered as a standard method in time pressure experimental studies (Bertola et al., 2012; Gelau et al., 2011; Paschalidis et al., 2018; Pawar and Velaga, 2020; Rendon-Velez et al., 2016). However, there exists a high chance of learning effects. Therefore, a repeated measures ANOVA and post hoc test was conducted on reaction time to examine the influence of learning effects. The results showed insignificant effects of fixed order on reaction time ($F(2, 774) = 2.237$, p-value = 0.11). Thus, it can be concluded that repeated data collection in fixed order had insignificant effects on driving behavior of the drivers (Pawar and Velaga, 2020). The current study specifically focused on driving behavior at the onset of yellow signal at four-legged signalized intersections. In future, similar research can be carried on three-legged signalized intersections where driving behavior during yellow signal and red signal can be examined under time pressure driving conditions. A fixed-base driving simulator was used in this study to conduct the experiments. In future, researchers can conduct experiments on moving-base driving simulators to obtain better insights on acceleration behavior of the drivers under various time pressure driving conditions.

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